To Follow the Market or the Parent System: Evidence from Health IT Adoption by Hospital Chains

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Abstract

I study how hospital chains consider the tradeoff between internal and external network benefits in technology adoption. I estimate a discrete-choice model that characterizes adoption decisions using a national sample of U.S. hospitals from 2005 – 2014. After instrumenting a vendor's market and system shares, I find affiliated hospitals tend to choose the internally preferred vendor, but experienced adopters also welcome external popular options. Factors affecting the tradeoff include chain size and the need for internal coordination. The stronger incentives for internal integration in health IT adoption among chains might create frictions to sharing information externally.

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1 Introduction

Information technology (IT) adoption has become a critical activity in many industries, and connectivity is an increasingly important function in the usage of IT. In the presence of various incompatible products, the choice of technology depends not only on its usability and quality, but also on the entities that can be communicated with. The adoption decision for multidivisional organizations could be complex. On the one hand, choosing a vendor that is commonly adopted within the organization can increase returns to scale and potentially improve efficiency in communication, the benefits related to *internal network effects*. On the other hand, the parent system may let its subsidiaries actively respond to external local conditions—such as adopting the local popular technology to better coordinate with external neighboring firms—to capture the benefits from *external complementarities*. This paper studies the strategic effect on the adoption choice of electronic medical records (EMRs)—the central component of health IT infrastructures—among hospital chains, whose decision could involve the tradeoff between the internal and external network externalities. Analysis results shed light on the strategic management of large healthcare organizations and have potentially important policy implications for coordinating the adoption of health IT.

EMRs allow healthcare providers to store, retrieve, and exchange health information using computers instead of paper records. Many EMR systems are not interoperable, but hospitals affiliated with the same chain benefit from purchasing from the same vendor in many respects. First, they can enjoy economies of scale by sharing the licensing fee, human-capital training materials, costs of external consultancy, expenditures on IT support services, and so on. Or the vendor may simply offer discounts to affiliated members to win the entire chain. Moreover, although sharing

the same vendor does not ensure interoperability,[1] systems from the same vendor can communicate with each other relatively easily. Thus, the efficiency gains in transferring information when it is needed, could increase with the number of affiliated providers on the same vendor platform.

Note that hospitals on a common vendor platform may still have challenges in data transmission. For instance, hospitals could customize the implementation, resulting in heterogeneity between hospital EMR systems even though they come from the same vendor. In this case, information transfer between them may not be seamless.[2] Therefore, a market (chain) that is dominated by a particular vendor does not necessarily imply that market-wise interoperability (chain-wise uniformity) has been achieved. However, I view the efficiency gains in communication between hospitals choosing the same vendor as a potentially important source for network benefits, as studies have found that hospitals using a common vendor system face fewer technical barriers to establishing connections (Everson, 2017) and are more likely to engage in health information exchange activities (Everson and Adler-Milstein, 2016; Downing et al., 2017; Castillo et al., 2018).[3]

However, a subsidiary may have to forgo the similar cost savings and/or efficiency gains from the external local market if it sticks to the internally preferred vendor who is not popular in the local market. For instance, the local market-dominant vendor—the one that local hospitals most commonly adopt—might provide promotions to local hospitals or achieve economies of scale in the provision of similar products and services, which can translate into a cost advantage. Ad-

[1]Interoperability describes the ability of different information systems, devices, and applications to access, communicate, integrate, and interpret data in a coordinated manner (https://www.himss.org/resources/interoperability-healthcare).

[2]Appendix Table A2 shows that hospitals could purchase different products within an integrated EMR system for customization.

[3]Healthcare providers that share a common vendor platform typically face *fewer* barriers to achieving interoperability (Everson, 2017). Many recently developed informatics tools and approaches rely on a *vendor-based* system, and thus, data access and exchange is expected to be easier on platforms from the same vendor (EDM Forum, 2013).

ditionally, hospitals may experience greater demand for information exchange with neighboring, non-affiliated hospitals. Choosing the same vendor platform with neighboring healthcare providers might reduce the additional costs of transmitting data externally—such as printing/faxing patients records or installing "extra" interfaces to connect to external providers that use different EMR systems. Moreover, the customization and support for EMR implementation could be complex and labor intensive; and thus, it may be better to have a local IT provider and reply on local resources (e.g., skilled labor and infrastructure) that could work as a substitute for internal support (Forman et al., 2008). Decentralizing IT solutions of the chain allows its subsidiaries to choose the technology in response to local conditions to optimize the performance.

Nevertheless, using the same vendor platform as other local providers may not be beneficial, due to competition concerns. When data transmission becomes relatively easy, hospitals may worry about losing patients, especially those with insurance plans that set less stringent rules for referral. For instance, the likelihood of losing a patient who is seeking a second evaluation or considering a different provider becomes higher if information can be accessed without barriers. Studies have found that making access to medical records hard may reduce the likelihood of patients switching providers (Baker et al., 2015). However, this effect could be small, because it does not seem to be the primary finding in closely related studies.[4]

Decision-making for affiliated hospitals involves the tradeoff between the gains from internal network effects and those from external local adaptation, especially when the benefit from external

[4]For instance, when the network definition accounts for vendor differences, both Desai (2016) and Lin (2021) find a positive correlation between the probability of choosing a vendor and its local market share. Moreover, empirical evidence suggests that hospitals are more likely to exchange patient records if they share a common EMR system (Everson and Adler-Milstein, 2016; Downing et al., 2017; Castillo et al., 2018). One exception is the paper by Wang (2021), who finds the competition effect dominates when considering different levels of adoption, but her analysis does not account for vendor heterogeneity.

complementarities outweighs the competitive effect. I study how affiliated hospitals consider these tradeoffs from their choice of EMR vendors. Specifically, I use a discrete choice model to examine how the probability of choosing a particular vendor changes as the vendor's local market share or system share varies, assuming no strategic interaction between hospitals and vendors. The local *market share* is defined as the ratio of the total number of local hospitals adopting this vendor to the total number of hospital adopters in the local market. The *system share* is defined as the fraction of affiliated hospitals adopting this vendor among all member hospitals with EMRs.

This paper is one of the few empirical studies documenting these dynamics behind the technology adoption decision in the context of health care—an ideal and important setting for this topic for several reasons. First, this industry is information-intensive: the provision of care relies on substantial intra- and inter-organization interactions. Hospitals' decision to adopt health IT plays an important role in the strategic interaction between all healthcare providers.

Moreover, understanding the interplay between these incentives is important because of different policy implications and because of the large dollar values at stake. By 2015, the U.S. federal government had spent over $20 billion[5] to promote the adoption of EMRs, with the goal of building a nationwide health information network, but a truly interoperable healthcare system has yet to be established. If hospitals demonstrate incentives for external coordination, policymakers may consider minimal interference. However, if these hospitals demonstrate strong preferences for the internally preferred vendor, which might create frictions to external information sharing and even result in anti-competitive practices, such as information blocking,[6] policymakers may have to con-

[5]See https://www.healthcareitnews.com/news/ehr-incentives-climb-19b.
[6]See https://www.healthit.gov/sites/default/files/reports/info_blocking_040915.pdf.

sider (re)designing appropriate policy and subsidy mechanisms to encourage outside cooperation.[7] Finally, the tradeoff studied here has analogies to the consideration in other industries, such as software, telecommunication, computing and network equipment, and so on. The analysis and implications could be applied to a broader context.

Based on a national sample of hospitals from 2005 to 2014, I estimate a multinomial conditional logit regression of hospital choice over vendors and find that, in general, the value of a particular vendor increases with its popularity in the local market and among all affiliated hospitals, with the latter being much more significant. However, endogeneity could arise due to unobserved characteristics at the market or chain level. For instance, a vendor achieving local (within-chain) dominance could simply result from market-wise (chain-wise) promotions instead of benefits from external (internal) network effects. I use instrumental variables (IVs) for both the market and system shares. The idea is to exploit the cross-market (cross-chain) spillover within a chain (market) to construct the IVs. I use the control function (CF) approach in the IV estimation.

After addressing endogeneity, affiliated hospitals show even stronger incentives to choose the internally preferred vendor. The positive effect at the market level disappears for new adopters but becomes larger and more significant for experienced adopters. A potential explanation is that hospitals with existing EMRs have accumulated experience with the technology and have a better sense of what complementary resources are available nearby. I also explore what factors could affect the extent to which an affiliated hospital responds to the market-level and chain-level vendor prevalence. For instance, I find that a larger chain is more likely to work with a single vendor,

[7] Even though most hospitals have acquired EMRs by the end of the studied period, learning about the balance between these strategic imperatives remains important because of the increasing trend of switching and the ongoing policies for health IT diffusion.

but member hospitals surrounded by many affiliated, complementary facilities tend to be more responsive to external local market forces.

The finding of stronger incentives for internal integration in EMR adoption among hospital chains has potentially important policy implications. Intuitively, it tends to be easier to coordinate health IT adoption for hospitals belonging to the same chain than for different hospitals. However, if affiliated hospitals are inclined to follow the parent system and if different chains have different internally preferred vendors, it might create frictions to exchanging patient information at the market level, and policy makers might consider approaches to incentivizing external coordination in health IT adoption. For instance, a regional public agency or a public health IT platform at the state level could be established to facilitate interoperability across all hospitals.

Related literature. This paper is related to four strands of literature. First, it contributes to the current studies on EMR adoption built on network effects theory (Miller and Tucker, 2009; Lee et al., 2013; Wang, 2021). Most prior studies explore the network effect from EMR adoption by studying how the fraction of nearby adopters affects a hospital's adoption probability. My paper further examines how the benefits from choosing the same vendor—not just from general adoption—affect the adoption choice of vendors, by recognizing the heterogeneity between vendors. Both Desai (2016) and Lin (2021) also account for vendor heterogeneity in their papers, but they focus on the benefits derived at the market level. I further examine the tradeoff between the gains from choosing the external popular vendor and the benefits from choosing the vendor widely adopted within the chain.

Second, this paper contributes to the empirical literature on technology adoption with network effects (Goolsbee and Klenow, 2002; Gowrisankaran and Stavins, 2004; Tucker, 2008; Björkegren,

2019), by exploring the mechanisms that underlie how organizations with multiple segments evaluate different levels of network effects. In addition to the main analysis, I also examine to what extent, factors such as economies of scale or demand for internal coordination affect the tradeoff hospital chains face. Third, this paper also provides empirical evidence to the literature on how organizations decide between internal coordination and external adaptation. A rich body of theoretical studies investigates this tension using team-theoretic models (Dessein and Santos, 2003, 2006; Dewatripont, 2006; Alonso et al., 2008; Rantakari, 2008), but empirical evidence has been rather limited due to data constraints. My approach to exploring the underlying mechanisms is similar to that by McElheran (2014), who examines what factors are associated with (de)centralized IT investment, based on a national sample of U.S. manufacturing firms. Finally, this paper also complements the broad literature on IT diffusion that investigates how business characteristics affect IT investment decisions via its impacts on costs and benefits (Forman and Goldfarb, 2006; Forman et al., 2008; Dranove et al., 2014). Motivated by these studies, my paper examines how hospital systems balance the internal constraints and external market forces in IT purchasing.

The rest of the paper proceeds as follows. Section 2 introduces the industry and institutional background. Section 3 presents the datasets and shows summary statistics. Section 4 explains the empirical strategy. Section 5 discusses the estimation results. The last section concludes.

2 Industry Background

EMRs were invented in the 1970s, but their acceptance was slow until recent years. In 2009, the American Recovery and Reinvestment Act provided $27 billion to promote health IT—in par-

ticular, to encourage the adoption of EMRs. It was the first substantial commitment of federal resources to support the adoption of this technology and created a strong push in the diffusion. I focus on inpatient EMR systems, particularly on the component, clinical data repository (CDR). CDR is essentially a centralized database that collects, stores, and reports health information. It is the backbone of the entire system.

The implementation cost of an EMR system varies tremendously depending on numerous factors, including the sophistication of the system, the amount of data conversion, the level of customization, one-on-one assistance during training, and ongoing use. According to a study conducted by the Congressional Budget Office (Orszag, 2008), the average implementation cost for a 250-bed hospital ranges from $3 million to $16 million. The rollout cost could even escalate to hundreds of millions of dollars for large hospitals. After the initial implementation, the annual cost for subsequent upgrades and maintenance ranges from 20% to 30% of the initial contract value.

Despite the hefty price tag accompanying EMR implementation, hospitals are willing to make massive investments in this technology for various reasons. Besides the strong push from the federal incentive program, EMRs enable hospitals to engage in better documentation, to lower the administrative costs, and to streamline and automate the revenue practices. Digitizing medical records also helps hospitals adapt to recent payment reforms, as well as to the new features of accountable care organizations. Finally, a qualified EMR system may improve the quality of health care, although the literature provides mixed evidence overall, or positive effects among subpopulations.[8] Existing adopters may consider replacing the current EMR vendors, even though the new purchase and implementation involve considerable costs and efforts. According to Coustasse et al.

[8]See Atasoy et al. (2019) for a comprehensive review.

(2018), the three most salient reasons for switching EMRs include poor performance of the current system, desire for interoperability, and excessively high costs of maintenance or upgrades.[9]

Choosing between EMR vendors is a complicated decision. Najaftorkaman et al. (2015) identify 17 distinct theories and models as theoretical foundations for EMR adoption studies and document 78 factors that influence adoption. Among those factors, technical factors (Van Der Meijden et al., 2003), financial factors (Simon et al., 2007), and organizational and environmental factors (Kazley and Ozcan, 2007; Jha et al., 2009; Miller and Tucker, 2009; Angst et al., 2010) have received significant attention in the health informatics and economics literature. I focus on an environmental factor, the network effect, which reflects strategic interaction in the adoption decision.

According to the American Hospital Association (AHA), a hospital chain/system is defined as "either a multi-hospital or a diversified single-hospital system."[10] It could consist of multiple hospitals (in which case, the chain is not vertical integration) or include both hospitals and affiliated healthcare organizations that provide non-hospital care services—such as ambulatory care facilities or subacute care units—a case similar to vertical integration. Ambulatory care facilities offer medical services that do not require an overnight hospital stay (Hirshon et al., 2013). Subacute care refers to a level of care that is intensive—but to a lesser degree than hospitalization care—and is usually rendered to patients right after acute hospitalization for rehabilitation or continuous treatments. These facilities provide services complementary to hospital care. Thus, their consolidation with hospitals could imply greater demand for internal coordination.

More often than not, affiliated hospitals (and affiliated non-hospital facilities) are managed by

[9]Switching may also happen due to market exit of an existing vendor, but it is not the primary reason as shown in the data. I provide more detail on exits of EMR vendors in Appendix 1.

[10]See Fast Facts Archive 2019 from the AHA Annual Survey (http://www.aha.org/research/rc/stat-studies/fast-facts.shtml).

a central organization. The organization structure of a hospital chain could be rather complex and varies substantially by chain. Although no dominant organization structure exists, some common elements do: the board of trustees/directors that governs the entire organization; hospital administration, which includes different levels of managers; medical staff consisting of physicians and nurses who provide medical services; and so on.

The investment in health IT imposes non-trivial changes to the entire organization and has become part of strategic planning at the organization level (Vassolo et al., 2021), the decision for which usually involves the top level of decision-makers—the board and the executive team. There is no consensus on the appropriate level of control and authority of the parent board over its affiliates, but the best practice seems to encourage the governance structure to leave room for local sites to make decisions regarding competition and asset investment. In this paper, I assume that the action is taken by the individual hospital, which reflects the chain's adoption incentive. I provide more detail on the organization structure of hospital chains in Appendix 1.

3 Data

3.1 Data sources and important variable definitions

My primary dataset comes from the Healthcare Information and Management Systems Society (HIMSS) Analytics Database, which is the longest running survey and comprehensive national source of health IT adoption data. The database contains detailed demographic and IT profile information for the majority of U.S. hospitals and a large set of non-hospital facilities. It records the time and choice of the adoption decision for these healthcare providers.

I define a hospital as having adopted EMRs if the component CDR is live and operational in the hospital. Other typical and common applications will often be put in place after CDR,[11] usually purchased from the same vendor. This paper seeks to evaluate the strategic effect on the choice of vendors, which is considered at the early stage of the adoption decision. The time to adopt CDR signals a hospital's willingness to enter the market and its preference for a particular vendor. With the information on vendor identity, I construct the dependent variable—the choice of a particular vendor by an affiliated hospital. A hospital becomes a new adopter in a particular year if its initial adoption of EMRs takes place in that year, whereas a hospital already with EMRs in that year is categorized as experienced adopters. I use a vendor's market (system) share to measure its prevalence at the market (chain) level, which is defined as the fraction of local (member) hospitals choosing this vendor among all adopting local (member) hospitals. The vendor with the highest market (system) share is called the market-dominant (system-dominant) vendor.

The HIMSS data include key demographic information about hospitals/chains, such as number of bed and location. The database also includes the number of ambulatory and subacute care facilities associated with a healthcare delivery system. I complement the HIMSS data with the AHA Annual Survey (which is available for a shorter time period between 2005 and 2010), using the Medicare provider number and geographic information to link the datasets. I extract variables related to profit status, location, and whether a hospital is a teaching hospital from the AHA data.

A market is equivalent to a health service area, a measure developed by Makuc et al. (1991). A health service area consists of one or more counties that are relatively self-contained with respect to the provision of routine hospital care. The location of each hospital can be directly linked to the

[11] In the sample, more than 95% of hospitals with advanced components have already adopted CDR.

corresponding health service area by the federal information processing standards code. Following prior studies, I control for market characteristics that are related to healthcare market competition and also affect hospital adoption decisions, using the following two variables: the size of the local elderly population and the Herfindahl-Hirschman Index (HHI) (Lin, 2015; Wang, 2021). I obtain the former from the Area Health Resource Files. As suggested by Lin (2015), the size of the elderly population can serve as a measure of the demand for health care. I construct the HHI using the number of total admissions in each hospital. Including HHI controls for the effect of the competitiveness in the hospital market on the adoption decision.[12]

Sample construction. The AHA annual survey contains over 5,700 hospitals each year. After merging it with the HIMSS dataset, I obtain about 4,500 hospitals.[13] The market share is calculated based on all hospitals (both stand-alone and affiliated hospitals), but the main analysis focuses on the adoption choice of affiliated hospitals, about 55% of the whole sample. To summarize, the sample contains approximately 2,500 hospitals affiliated with 420 hospital chains, covering more than 920, or 95%, of the health service areas in the U.S. between 2005 and 2014.[14]

3.2 Summary statistics and suggested evidence

Figure 1 presents the trend of adoption and switching rates separately for stand-alone and affiliated hospitals. Almost 49% of affiliated hospitals adopted EMRs in 2005, and the fraction had risen to over 98% by 2014. Switching rates had been increasing from 4% to over 10% at the end of the

[12]Other variables may also play an important role in the competition of healthcare markets and potentially influence the adoption decision. I use only these two variables, because they are commonly cited as important factors for healthcare competition, and I also want to keep the estimation manageable.

[13]The hospitals in the merged dataset are slightly larger and more likely to be teaching or not-for-profit hospitals, as shown in Appendix Table A5, where I compare certain hospital characteristics between the merged dataset and AHA data. The implications from the analysis in this paper mainly apply to the hospitals in the sample.

[14]I focus on this sample period, due to limited information on hospital system affiliation in later years.

sample period. Stand-alone hospitals share a similar pattern in adoption but switch less frequently.

Figure 2 shows the distribution of the adoption choice between the market- and system-dominant vendors by affiliated hospitals, for which none of the dominant local vendors is the main IT provider for the parent system. Thus, these vendors fall into one of the following categories: dominating the local market, dominating the parent system, or neither. Almost 60% of new adopters follow the parent system, whereas less than 10% choose the dominant local vendor. For experienced adopters, the difference between the percentage of choosing the market- and system-dominant vendors becomes less significant, although a large fraction of switchers end up with vendors other than these two options.

The market for inpatient EMRs has been fairly concentrated. Appendix Table A1 lists the top 11 vendors that, on average, account for over 90% of the national market share. All the remaining vendors are categorized into one group called "others." The combination of the leading vendors in Appendix Table A1 with the group "others" results in 12 options that form a choice set available to all hospitals. Local markets are even more concentrated. In over 60% of the markets, no more than three existing vendors per market belong to the top list (shown in Appendix Figure A1), and the market-dominant vendor usually has at least 50% of the local market share (shown in Appendix Figure A2).[15] Also, most markets have a clear dominant vendor, but which vendor dominates varies across geographic areas, as shown in Appendix Figure A3. Similarly, in about 80% of the hospital chains, no more than two leading vendors are in place (shown in Appendix Figure A4), and at least 50% of adopting members choose the system-dominant vendor (shown in Appendix Figure A5).[16] To summarize, the simple statistics suggest that integration occurs both externally

[15]This finding holds for most of the leading vendors except GE.

[16]This finding holds for most of the leading vendors except Healthland.

and internally, with the latter to a greater extent. Also, variations in adoption choice across markets and chains are important sources for identification.

Table 1 reports the summary statistics for hospital characteristics. Consider the upper panel for new adopters or hospitals that had not adopted EMRs by the end of the sample period. The first row shows how the fraction of new adopters changes over time. Over 8% of affiliated hospitals were new adopters in every year between 2005 and 2008. However, the fraction dropped to 1.7% or lower after 2008. The next two rows suggest that both markets and hospital systems are becoming more connected. Particularly within a chain, the choice of more than 70% of adopting members converges to the system-dominant vendor at the end of the sample period. The other hospital characteristics, such as profit status, percent of teaching hospitals, and number of beds, remain stable over time. I also report the percentage of affiliated non-hospital facilities in the same market as an affiliated hospital and find that, on average, 25%-30% of these facilities are nearby. The lower panel suggests that experienced adopters, on average, are larger, more likely to be teaching hospitals, and surrounded by affiliated facilities.

Table 2 reports the statistics at the chain and market level, respectively. The chain size, in terms of the total number of hospitals or beds, grew during the sample period. More leading vendors exist per chain over time. The number of affiliated ambulatory care facilities per chain doubled during the sample period, which is consistent with the recent growth in the outpatient setting—hospitals reducing inpatient care by shifting patients to outpatient facilities. The last panel summarizes the variables at the market level. In general, there are more affiliated hospitals than stand-alone hospitals per market. The elderly population increased by 25% from 2005 to 2014, and the HHI remained stable during this period.

4 Estimation Strategy

4.1 Non-IV estimation

The empirical specification is motivated by the technology adoption decision facing a stylized affiliated hospital, which chooses from a set of vendors that produce incompatible EMR systems and picks the most profitable one among those generating positive profits. The payoff from choosing a vendor depends on a variety of factors. I focus on the effect of network benefits at different levels and estimate a static discrete-choice model using the multinomial conditional logit specification. The probability of hospital i—without EMRs—choosing vendor j in year t has the following form:

$$\text{Prob}\left(D_{it}^{j}=1\middle|X_{it-1}^{j},W_{it-1},\mathcal{M}_{it-1}\right)=\frac{\exp\left(X_{it-1}^{j}\alpha+W_{it-1}\gamma^{j}+\mathcal{M}_{it-1}^{j}\right)}{1+\sum_{k\in\mathcal{J}}\exp\left(X_{it-1}^{k}\alpha+W_{it-1}\gamma^{k}+\mathcal{M}_{it-1}^{k}\right)}, \tag{1}$$

where $D_{it}^{j}=1$ if hospital i chooses vendor j; X_{it-1}^{j}, W_{it-1}, and $\mathcal{M}_{it-1}$ denote the *lagged* vendor, hospital, and market characteristics, respectively; $\mathcal{J}$ represents a set of vendors available to all hospitals, including the leading vendors as listed in Appendix Table A1 and the "others." Given that most of the vendors serve the national market, I assume that $\mathcal{J}$ is fixed for every hospital. Note that not all vendors are likely to be equally accessible to every hospital/chain. I make the assumption for simplicity and also considering a recent trend that vendors are seeking a wide variety of customers.[17] Note that, the adoption decision can be conceptualized as proceeding in two steps: whether to adopt any EMRs and then which vendor to select. For simplicity, the current

[17]For instance, certain vendors that used to target large hospitals start to approach small or community hospitals (https://www.healthcareitnews.com/news/now-epic-goes-small). However, in cases where only a subset of vendors is available in certain locations or to certain hospitals/chains, the current setup does not distinguish between a vendor being unavailable or not being chosen, which could be a limitation.

specification conflates these two dimensions of decision-making and treats non-adoption as the outside option. I describe a simple model underlying hospitals' choices of EMR vendors and provide more discussion about this potential issue in Appendix 2.

X_{it}^{j} includes a set of vendor j's characteristics. Let

$$X_{it}^{j}\alpha = \text{MktShare}_{it}^{j}\alpha_{\text{mkt}} + \text{SysShare}_{it}^{j}\alpha_{\text{sys}} + \sum_{\ell \in \mathcal{J}} [\mathbb{1}\{\ell = j\}(\alpha_{\ell} + \varphi_{\ell} \times t)] \tag{2}$$

$$+ \mathbb{1}\{i \text{ has EMRs}\} \times \mathbb{1}\{j \text{ was chosen at } (t-1)\}\, \alpha_{\text{chosen}},$$

where MktShare_{it}^{j} and SysShare_{it}^{j} denote the share variables; the third term on the right-hand side incorporates vendor fixed effects and vendor-specific time trends, with the former controlling for other unobserved vendor characteristics[18] and the latter capturing the overall changes in vendor quality/promotion/popularity over time.[19] For hospitals with EMRs, to control for the switching incentive, I further include an indicator for whether a particular vendor was previously chosen.

The goal of this study is to examine the tradeoff between different levels of network benefits, but the estimated α_{mkt} (α_{sys}) could also be affected by the discounts offered by the vendor or the interaction between the vendor and hospital/chain, such as negotiation. To minimize these confounding effect at the market (chain) level so that α_{mkt} (α_{sys}) *only* reflects the external (internal) network benefits, I use IVs in the estimation and provide more detail in the next section. A significantly positive coefficient for market (system) share suggests a member's tendency to adopt the externally (internally) popular vendor, due to network benefits rather than other reasons

[18] Such characteristics include IT capabilities at the vendor level, namely, system quality, usability, functionality, and technical support, among others.

[19] An arguably better way is to include vendor-year fixed effects to allow for unrestricted, differential trends by vendor, but it would result in many more parameters and make the estimation less precise.

such as vendor promotion. If the concern about losing patients exceeds the benefit from external complementarities or if the pursuance of internal network benefits dominates, I expect the profit from adopting the dominant local vendor to diminish or even turn negative. Therefore, comparing α_{sys} with α_{mkt} suggests how an affiliated hospital assesses the network benefit from choosing the internally preferred vendor versus the network benefit from the externally popular vendor.

In theory, the network benefits, both internal and external, can arise from (1) cost savings in implementation and operation that could be due to increasing returns to scale[20] or (2) potential efficiency gains in information transfer with other (affiliated or non-affiliated) healthcare providers. Distinguishing one mechanism from another is beyond the scope of this paper.

I control for the following hospital characteristics (encapsulated in W_{it}): profit status, number of beds, and whether a hospital is a teaching hospital.[21] I further interact vendor dummies with number of hospital beds—to allow the effect of this variable to vary by vendor.

I control for market characteristics (encapsulated in $\mathcal{M}_{it}^{j}$) following the approach by Lin (2015) and Wang (2021). I include the following two market observables: total elderly population and the HHI. I control for market unobservables using market-level group dummies, similar to the method used by Collard-Wexler (2013), Lin (2015), and Wang (2021). I construct these group dummies in the following steps. First, I regress the share of adopting hospitals in each market on the observed market characteristics (i.e., the size of the elderly population and HHI) and market and year fixed effects. I divide all the markets into four groups by quartiles of the estimated market fixed effects,

[20] I categorize increasing returns to scale into network benefits, because the cost savings here are essentially economies of scales, which are closely related to network effects (Farrell and Klemperer, 2007).

[21] I tested what to include in the controls from a set of relevant variables mentioned in the literature (using a shorter period of the sample), including total outpatient visits, total inpatient admissions, the number of full-time physicians, percentage of Medicare and Medicaid discharges, number of competitors, and fraction of competitors with EMRs. The results are robust to those from the reported specification.

which indicate the level of profitability on adoption. Then, I include three dummies (for the top three quartiles) in the main regressions. Following prior studies, I call the market-group dummies market-category effects.

The choice set for hospitals without EMRs includes the leading vendors as listed in Appendix Table A1, the "others," and the outside option—no EMRs. I exclude the outside option from the choice set for hospitals already with EMRs. Note that I estimate a static instead of dynamic model here, considering that the choice of brands might require less dynamic optimization than the fundamental decision of acquiring an EMR system. Prior studies have applied a similar approach to model technology adoption with network effects (Gowrisankaran and Stavins, 2004; Desai, 2016). I expect the results from a dynamic model to be qualitatively similar, but predicting the difference in magnitude, which could depend on a variety of factors, is difficult.[22]

I use the maximum likelihood estimator and estimate the multinomial conditional logit model separately for hospitals with and without EMRs. Each observation corresponds to a hospital-year combination. In the analysis for new adopters, a hospital is dropped after adoption; the analysis for experienced adopters is based on all hospital-year cells among hospitals with EMRs. Standard errors are clustered at the chain level to allow for dependence in the residuals across member hospitals within a chain.

4.2 IV estimation

Concerns may exist about endogeneity for the market share variable, such as market-wise promotion or special preferences of local physicians, both of which could simultaneously affect the

[22] Lin (2021) compares the estimated external network benefits between the static and dynamic models, based on the sample of stand-alone hospitals. She finds that the main effect remains in the dynamic model but becomes smaller.

market share and the choice of vendors at the same time. For instance, a vendor based in a particular market may offer promotions to all local hospitals. It thus becomes the most adopted simply because of the price advantage rather than the network benefits. Moreover, similar endogeneity could also exist in system share. To address these concerns, I construct IVs for both the market and system shares.

IVs for market share. I exploit the cross-market spillover within a hospital chain. Specifically, I first identify all the *outside associated markets*, defined as the external markets that are "important" to an associated chain—the one that has affiliated hospitals in the same market as the focal hospital. I view a market as "important" for a hospital chain if, among all the markets where the chain is located, this market includes the most of its hospital members. Then, the instruments are constructed by averaging the market share and market dominance indicator for each vendor across these markets. The key identifying assumption here is that these IVs affect the focal hospital's vendor choice only via their effects on the local vendor market share. For instance, there should not be any common shocks affecting the demand for vendors in the data that are not captured by the controlled variables or the fixed effects. I provide more detail on how to construct the instruments and discuss the exclusion restriction assumption in Appendix 3.

Appendix Figure A6 shows an example of outside associated markets for an affiliated hospital in the actual data. The focal hospital is located in Florida, and some of its local competitors belong to chains with member hospitals in other regions: one in Mississippi, one in New York, and one in Pennsylvania. It is relevant in the sense that the associated chains' decision-making may take into account the conditions in these markets (because they are important markets), which will affect the choice of their members and, ultimately, the focal hospital. It is exogenous because

these outside markets plausibly have little relation to the unobservables in the focal market. To ensure the exclusion restriction assumption holds, I include in the IV sample the markets that are "unimportant" for the associated chain, that is, the markets with some but not the most of its member hospitals. I also confine the outside associated markets to those located at least 180 miles from the focal hospital to avoid spillovers across markets due to proximity.

Note that the market share could also suffer from endogeneity arising from simultaneity, due to the unobserved price and quality of EMRs. However, the simultaneity bias might not be substantial since I use the lagged market share as the key variable of interest. The IVs defined above have the potential to reduce the simultaneity bias, assuming that vendors do not adopt an across-the-board pricing strategy. Without this assumption and the assumption that the period-to-period decisions are made independently, the proposed IVs might not completely correct the simultaneity bias, which could be a limitation in the paper. I provide more discussion on this issue in Appendix 3.

IVs for system share. Using a similar idea, I construct the IVs for system share based on *associated chains*—the ones sharing common markets with the focal chain. Specifically, I first identify all the associated chains for a given chain, and then calculate the average of the system share and system dominance indicator for each vendor across these chains. These IVs satisfy the relevance condition, because the adoption choices of the members in the associated chain will affect the choices of the focal chain via the overlapped market. They are exogenous to the focal chain in that the interaction between the associated chain and its chosen vendors is plausibly private and thus will be independent of that between the focal chain and its vendors.

Appendix Figure A7 presents an example of a focal chain and its associated chains from the data. The focal chain has two important markets: one on the northwest coast (shown in the left

subfigure) and the other on the southwest coast (shown in the right subfigure), with the latter containing hospitals from the associated chains that are widely spread out in the rest of the country. Appendix 3 contains more detail on these IVs, including their definitions and how I construct the IV sample to minimize the threats to the exogeneity condition.

I use the CF approach because of the nonlinear relationship. The first step is to respectively regress the endogenous variables—market share and system share—on the instruments and the exogenous variables described above. I obtain the error terms, $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$, respectively, from each of the equations. Next, I estimate the main regressions, additionally including the first-stage residuals and their polynomial expansion to the second degree.[23] The IV sample is restricted to the observations for which I can construct the instruments. I obtained the standard errors by bootstrapping to account for the estimation error in the first stage.

5 Results

5.1 Main results

I now discuss the empirical results. Table 4 reports the coefficients for the key variables of interest: market share, system share, and the indicator for whether a particular vendor was chosen previously. Column (1) suggests that, for new adopters, both the market and system shares have positive impacts on the adoption choice. The value from choosing the external popular vendor is less than that from choosing the internally preferred vendor. I also report the average marginal effect of each

[23] I provide more detail on the equations for the CF approach in Appendix 3.

share variable on the choice probability.[24] On average, the probability of choosing a vendor goes up by 19.4 percentage points given the variation in system share of this vendor, whereas the change in probability is 3.36 percentage points as the vendor's market share varies.

Column (2) shows the estimated coefficients from the regular logit regression based on the IV sample, for which the sample size drops by 64%, but the findings remain similar in the reduced sample, suggesting that the bias from sample selection is limited. Column (3) shows the estimates using the CF approach.[25] The coefficient for system share becomes larger, but the coefficient for market share is no longer significant. After controlling for the unobserved characteristics at the market and chain levels, the benefit from external (local) adaptation disappears for new adopters, suggesting either limited evidence of complementarities at the market level or significant competitive pressure that counteracts the gains from external complementarities.

The right panel shows the same set of results for experienced adopters. Column (4) shows that the coefficient on system share is significantly positive despite a smaller magnitude than that from the sample of new adopters, whereas the coefficient on market share becomes insignificant. I include in this analysis an indicator for whether a particular vendor was previously selected. The significantly positive coefficient suggests that the probability of choosing a particular vendor is highly associated with whether the vendor was previously chosen by the hospital. A potential reason is that the vendor might implement a non-linear pricing strategy—low (upfront) fixed costs and high variable costs—that generates a lock-in effect for its users. Note that this variable is likely

[24]To obtain the marginal effect, I first calculate the derivative of the choice probability with respect to the share variable. The derivative has a closed-form expression—a function of the predicted probability and the estimated coefficients—due to the assumption of the Type I extreme value distribution. The predicted probability varies by observation, and thus, the marginal effect is the average change across all observations.

[25]Table 3 reports the results from the first stage of the CF approach, suggesting that the instruments are strongly correlated with the endogenous variable.

to be endogenous due to unobserved price/quality, and thus, the estimate reflects an association rather than a causal correlation.[26]

The logit results are similar between the entire sample and the IV sample, except that the effect of system share seems to be greater among the IV sample. A potential explanation is that the effect of system share might be more significant among larger chains, because the average chain size in the IV sample is larger than that in the overall sample (compare the number of beds/affiliated hospitals in Table 2 with that in Appendix Table A4). The last column presents the results using the CF approach. The coefficients for both the system and market shares become significantly positive, with greater magnitudes than those from the non-IV estimation. On average, the change in system (market) share raises the probability of being chosen by 31.6 (9.53) percentage points.

Affiliated hospitals with existing EMRs seem to value external benefits to a greater extent than those without EMRs. A potential explanation is that new adopters tend to rely on internal experience or resources, due to the uncertainty about the technology, whereas existing adopters may have a better sense about the technology and what external complementary resources are available nearby, and thus, they are more likely to consider outside options.

The CF approach enables a heteroskedasticity-robust Hausman test on whether the suspected variables are endogenous. I conduct this test by testing the joint insignificance of the first-stage error terms included in the second stage. The last row shows that the null hypothesis of no endogeneity is rejected. The estimation model seems to fit with the data reasonably well, with the pseudo R^2 over 0.6 for initial adopters and over 0.8 for experienced adopters.

[26]Note that the model could also suffer from the initial conditions problem by including this variable, which can be hard to solve in nonlinear estimation (Wooldridge, 2005). In a sensitivity check, I exclude this variable and rerun the main specification. I present the results in Column (5) of Appendix Table A11. The main findings hold, except that the effect of market share becomes larger. I provide more detail in Appendix 3.

Robustness checks. I test the robustness of the results in the following ways. First, I construct the share variables accounting for hospital bed size (results in Appendix Table A6). I also use alternative market definitions, such as hospital referral regions (results in Appendix Table A7) or defining a market based on a 45-mile radius of the focal hospital following Lewis and Pflum (2017) (results in Appendix Table A8). I also rerun the main regressions on a shorter period (results in Appendix Table A9) or conditional on adoption/switching (results in Appendix Table A10). The main results hold. Second, I re-estimate the IV specifications due to various concerns related to endogeneity (results in Appendix Table A11), such as the endogeneity due to simultaneity, the bias due to sample selection, and the concern about the initial conditions problems and endogeneity. The findings are generally consistent. Third, I assess the robustness of the main results using different specifications by progressively adding more controls or fixed effects (results in Appendix Table A12). Finally, I examine how the effects of the share variables vary by certain market characteristics, such as hospital care market structure (results in Appendix Table A13) or market size (results in Appendix Table A14). I provide more details in Appendix 4.

5.2 Underlying mechanisms

I also explore the mechanisms that underlie the compromise in the choice decision. The idea is to examine whether the value of a vendor's internal/external prevalence depends on a moderating factor. Most of the analyses are indebted to the findings from the team-theoretic framework. The empirical approach is to additionally include interactions between each share variable and a moderator variable in the main specifications. I also estimate the baseline effect of the moderator variable. I report the results from IV estimation, where the CF approach is extended to allow for interaction

terms. Specifically, I introduce additional first-stage regressions in which the dependent variable is the interaction between the endogenous variable and the moderator variable, and the regressors include the instruments interacted with the moderator variable and other exogenous variables in the main regressions. In the second stage, I estimate the main equations using the maximum likelihood estimator, including all the first-stage residuals and their polynomial expansions.

Chain size

Acquiring and maintaining an EMR system is notoriously expensive. A natural choice for an affiliated hospital is to select the vendor that is widely adopted within the chain, so that members with the same vendor can apportion the fixed cost related to upfront investment, maintenance, subsequent upgrades, and so on. However, this argument is different from the prediction from the team theory literature that assumes a limited information-processing capacity of firms and thus anticipates that a larger (and more sophisticated) chain is more likely to decentralize IT purchasing, due to the high cost of information processing (McElheran, 2014).[27] To compare these predictions, I interact both the market and system shares with chain size, measured in terms of the total number of hospital beds in the chain, and include these interactions in the main regressions.

Table 5 presents the results, including the key variables of interest and the interactions with the moderator variable. The findings of the baseline effects are similar to those from the main specifications. The interaction term with system share is significantly positive among experienced adopters, suggesting that the larger a chain is, the more likely an experienced member is to adopt the internally preferred vendor. On average, the probability of a vendor being chosen given the variation in system share further increases by 0.942 percentage points for experienced adopters, as

[27] A third mechanism could be related to agency concerns, which lead to the same prediction as economies of scale.

the chain gets larger. To sum up, the large a chain is, the more likely its members are to follow the parent system, supporting the cost-saving incentive.

Need for coordination

The provision of health care usually involves multiple medical encounters, each of which will be more effective if all the related information can be accessed and coordinated. Thus, there is a need for information exchange between different healthcare providers, especially those serving different parts of the continuum of care. Also, information exchange is more likely to occur between providers in the same area, given that patients tend to seek care close by. Thus, a potential measure for the need for internal coordination is the fraction of affiliated ambulatory/subacute care facilities in the same market as the focal hospital.[28] I construct this measure using the HIMSS data.

However, there is an opportunity cost for a member hospital to follow the parent system, namely, the cost savings and potential efficiency gains the hospital could have received by choosing the local popular vendor. This cost could be significant for the entire chain if the member hospital is a relatively high-revenue division. This argument is consistent with the prediction from the team-theoretic literature: Member hospitals that are relatively more important—such as those of relatively larger size or contributing relatively greater revenues to the chain—have more discretion in the level of external local adaptation (McElheran, 2014). Thus, the presence of a large number of co-located, affiliated facilities that offer complementary services, on the one hand, implies a stronger need for internal coordination. But on the other hand, hospitals surrounded by these facilities have greater potential in generating relatively high revenue for the chain as these hospitals

[28]There could be other cases where affiliated units demand internal coordination. For instance, information exchange might also be important between affiliated hospitals providing similar/complementary services.

could be attractive to patients due to their ability to offer easier access to complementary services; thus, these members are more likely to appreciate external options.

To compare these propositions, I include in the main specification interactions of the measure for internal coordination and each share variable. Table 6 reports the results. Consider Columns (1) and (2) where the moderator variable is the fraction of co-located, affiliated ambulatory care facilities. The baseline coefficients for system share are slightly larger compared with those in Table 4, and the interaction among experienced adopters becomes significantly negative. Specifically, the increase in choice probability for this group due to higher system share declines by 3.75% (=1.26/33.6$\times$100%) after accounting for the fraction of affiliated ambulatory care facilities nearby. The results are similar when I construct the moderating variable using subacute care facilities, except that in this case, the coefficient for the interaction with market share becomes significantly positive among new adopters. Taken together, the results are more consistent with the second proposition: Following the parent system becomes less imperative for members that are potentially high-revenue generators.

I conduct several robustness checks to examine this mechanism. First, I replace the current moderating variable with the relative size of a member hospital to further examine whether the finding is in line with the prediction that relatively more important members have more discretion in the level of external local adaptation (results in Appendix Table A15) and find consistent evidence. Second, I test whether the results are likely to be driven by the case that vendors in markets with a larger number of healthcare providers tend to have smaller market share due to more intense competition (results in Appendix Table A16) and find that this can also be an explanation. Third, I examine whether the effect is more significant among hospitals treating complex patients and thus

requiring better information and labor coordination (results in Appendix Table A17). I provide more discussion in Appendix 4.

6 Conclusion and Future Work

In the presence of various incompatible IT systems, the adoption choice that hospital chains face involves a tradeoff between different levels of network effects. When the local popular vendor is different from the one preferred within the chain, I find that new adopters tend to go with the internal popular vendor. After controlling for the unobserved market and chain characteristics, the effect of market share becomes significantly positive for existing adopters, suggesting that hospitals with adoption experience might have more discretion in the level of external local adaptation.

When I explore the underlying mechanisms for the tradeoff, I find that affiliated hospitals from larger chains are more likely to share a common vendor platform, for which economies of scale could be an important reason. However, the likelihood of choosing the internally preferred vendor would drop for a member co-located with a large number of affiliated, complementary facilities.

In conclusion, I find that affiliated hospitals demonstrate strong incentives for choosing the vendor commonly adopted by other affiliated members than the one favored by external neighboring hospitals. The lack of interoperability between systems from different vendors could adversely affect competition and care coordination at the market level. Policy makers might consider policies to improve external coordination in health IT adoption.

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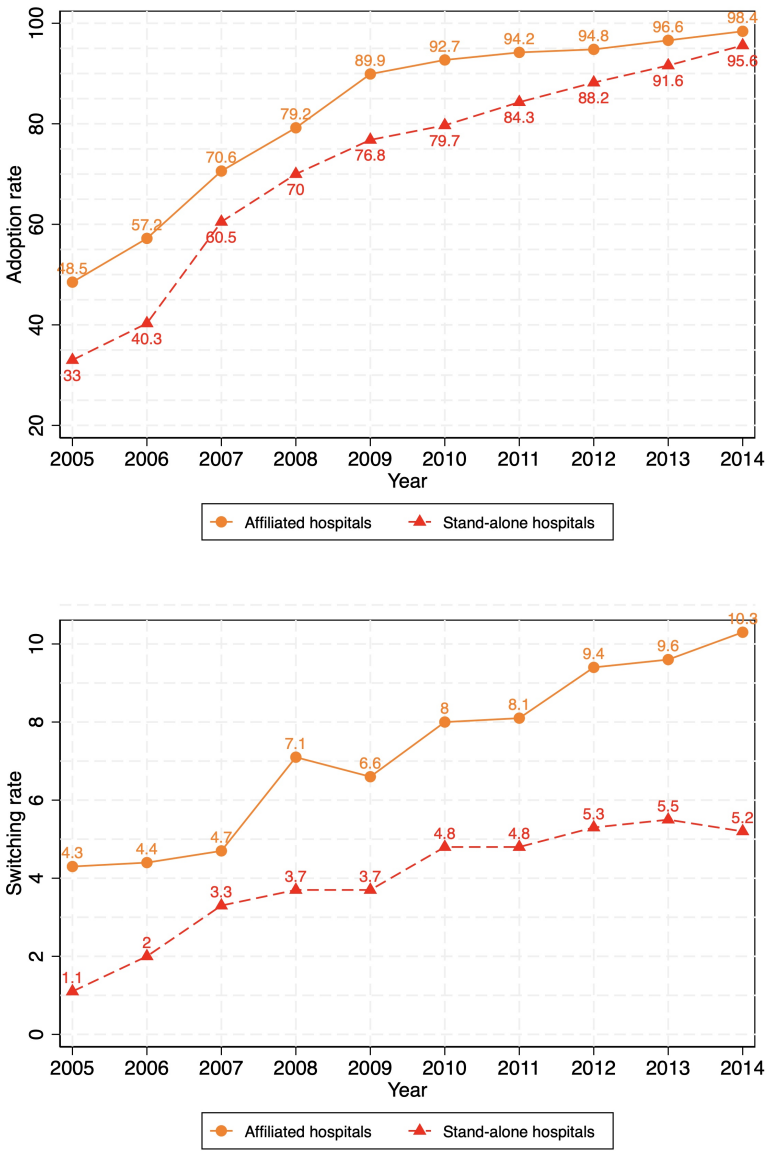
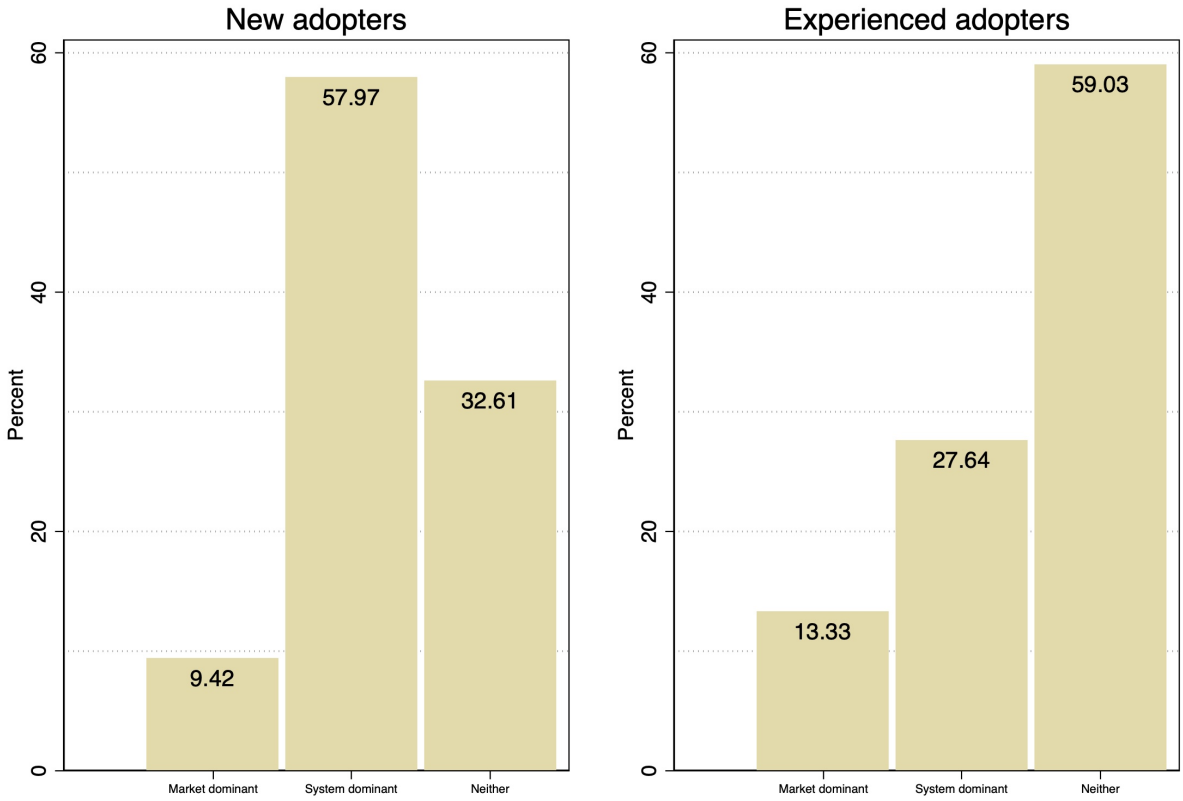
Figure 1: Adoption and switching rates (%) over time



Note: Upper panel shows the adoption rate and lower panel shows the rate of switching.

Figure 2: Frequency distribution of the choice of vendors



Note: Calculation based on affiliated hospitals for which no overlap exists between the set of market- and system-dominant vendors. There are 529 new adopters and 1,011 experienced adopters.

Table 1: Summary statistics for hospital variables by adoption status

New or never adopters	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
% new adopters	8.51	13.18	8.70	10.75	1.70	1.71	1.68	1.72	1.69	1.05
% whose chosen vendor is system-dominant	4.18	20.3	36.2	49.8	60.0	61.9	66.3	68.2	75.0	74.5
% whose chosen vendor is market-dominant	4.02	12.0	19.3	24.4	29.8	33.8	35.2	35.5	37.2	41.3
% ever not-for-profit hospitals	66.2	66.4	66.6	66.6	66.5	68.7	69.1	67.4	67.7	67.6
% ever teaching hospitals	6.03	5.99	6.00	5.96	5.98	6.18	6.10	5.96	6.02	6.10
# beds	190	189	188	187	189	193	192	190	191	191
% affiliated ambulatory care facilities in the same market	30	30.3	30.9	31.3	30.7	31.1	30.7	29.3	27.8	27.8
% affiliated subacute care facilities in the same market	28.2	28.9	29.3	29.8	29.3	29.3	29.8	28.2	25.1	25.4
Total # affiliated hospitals	1,244	1,253	1,250	1,259	1,255	1,214	1,213	1,241	1,230	1,213
Experienced adopters	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
% whose chosen vendor is system-dominant	73.9	76.5	76.5	73.6	72.1	73.6	72.4	72	75.2	69.5
% whose chosen vendor is market-dominant	37.95	38.8	37.8	37	34.8	35	35.8	35.9	36.8	39.3
% ever not-for-profit hospitals	65.9	66	66.4	66.6	67.6	68.2	68.6	68.6	68.8	69.6
% ever teaching hospitals	11.6	11.4	11.2	11.0	10.8	10.7	10.6	10.5	10.4	10.1
# beds	244	242	243	241	241	239	239	239	238	238
% affiliated subacute care facilities in the same market	38.1	37.1	37	37.9	38.3	37.3	36.7	36	34.3	33.8
% affiliated ambulatory care facilities in the same market	44.2	43.8	44.4	44.5	44.6	42.9	41.6	40.2	38.7	37.4
Total # affiliated hospitals	1,178	1,205	1,220	1,244	1,274	1,304	1,339	1,377	1,425	1,460

Note: Table reports the mean value of statistics over the years 2005-2014.

Table 2: Summary statistics for chain/market variables

Chain characteristics	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# affiliated hospitals	5.8	5.8	5.8	5.8	5.9	5.9	6.1	6.3	6.5	6.7
# beds	1,246	1,246	1,237	1,249	1,267	1,287	1,313	1,360	1,398	1,444
# markets	3.6	3.6	3.5	3.5	3.6	3.6	3.6	3.8	3.9	4
# leading vendors	0.8	1	1.1	1.3	1.3	1.4	1.4	1.4	1.5	1.5
# ambulatory care facilities	28	29	30	31	32	35	40	45	60	74
# subacute care facilities	4.8	4.6	5	4.5	3.8	3.6	4.1	4.4	4.6	4.7
Total # chains	421	424	429	428	429	424	421	415	411	401
Market characteristics	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# stand-alone hospitals	2.2	2.3	2.3	2.2	2.2	2.2	2.1	2	2	1.9
# affiliated hospitals	2.6	2.7	2.7	2.7	2.7	2.7	2.8	2.8	2.9	2.9
# leading vendors	1	1.2	1.6	1.8	2	2.1	2.2	2.2	2.3	2.3
# chains	1.6	1.6	1.6	1.6	1.7	1.6	1.6	1.7	1.7	1.7
Population over 65	39,930	40,241	40,958	41,989	42,904	43,829	44,844	46,766	48,418	50,142
HHI	0.55	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
Total # markets	915	921	921	921	921	921	920	920	920	919

Note: Table reports the mean value of statistics over the years 2005-2014.

Table 3: First-stage results in the CF

	Dependent variable: Market share		Dependent variable: System share	
	New adopter (1)	Experienced adopter (2)	New adopter (3)	Experienced adopter (4)
Market share in outside associated markets	0.229***	0.318***		
	(0.0133)	(0.00571)		
Market dominance indicator in outside associated markets	-0.0279***	-0.0522***		
	(0.00730)	(0.00281)		
System share in associated chains			-0.0788***	0.0713***
			(0.0218)	(0.0152)
System dominance indicator in associated chains			0.171***	-0.137***
			(0.0290)	(0.0188)
N	33,241	159,012	33,059	117,060
F-statistics	236.8	2043.8	23.78	38.46

Note: Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses, clustered at the chain level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect from share variables

	New adopter			Experienced adopter		
	All	IV sample		All	IV sample	
	Logit	Logit	CF	Logit	Logit	CF
	(1)	(2)	(3)	(4)	(5)	(6)
System share	2.729***	3.086***	4.586***	1.643***	2.348***	4.139***
	(0.170)	(0.124)	(0.413)	(0.129)	(0.255)	(0.305)
Market share	0.474***	0.627**	0.511	-0.127	0.242	1.248***
	(0.163)	(0.285)	(0.554)	(0.135)	(0.334)	(0.380)
Chosen previously				4.035***	3.815***	3.839***
				(0.0870)	(0.140)	(0.0840)
MEs (%): *System* share	19.4***	21.9***	32.6***	12.6***	17.9***	31.6***
	(1.20)	(0.878)	(2.94)	(0.988)	(1.95)	(2.33)
MEs (%): *Market* share	3.36***	4.45**	3.63	-0.969	1.85	9.53***
	(1.15)	(2.03)	(3.93)	(1.03)	(2.55)	(2.90)
N	56,147	20,007	20,007	251,940	75,900	75,900
Pseudo R^2	0.627	0.643	0.645	0.838	0.868	0.870
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$			0.00306			1.55e-12

Note: Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses. Standard errors clustered at the chain level for logit regressions and bootstrapped standard errors (based on 50 replications) for the CF approach.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect from share variables, by chain size

	Chain size	
	New adopter (1)	Experienced adopter (2)
System share	4.113***	3.734***
	(0.791)	(0.232)
Market share	1.344	0.867**
	(0.859)	(0.418)
Interacted with *system* share	0.0000175	0.0000269***
	(0.0000342)	(0.00000868)
Interacted with *market* share	-0.0000998	0.0000291
	(0.0000724)	(0.0000212)
Chosen previously		3.836***
		(0.0576)
MEs (%): *System* share (baseline)	29.2***	28.5***
	(5.62)	(1.78)
MEs (%): *System* share (extra)	0.653	0.942***
	(1.28)	(0.304)
MEs (%): *Market* share (baseline)	9.54	6.62**
	(6.10)	(3.19)
MEs (%): *Market* share (extra)	-3.74	1.02
	(2.71)	(0.742)
N	20,007	75,900
Pseudo R^2	0.647	0.870
P-value for joint signi--ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$	0.458	1.06e-16

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Unit of observation is hospital/year. Other regressors include the moderator variable, the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors (based on 50 replications) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect from share variables, by the need for internal coordination

	fraction of co-located *ambulatory* care facilities		fraction of co-located *subacute* care facilities	
	New adopter (1)	Experienced adopter (2)	New adopter (3)	Experienced adopter (4)
System share	4.731***	4.398***	4.419***	4.456***
	(0.427)	(0.275)	(0.412)	(0.303)
Market share	0.598	1.231***	0.303	1.336***
	(0.473)	(0.246)	(0.507)	(0.380)
Interacted with *system* share	-1.182	-1.533***	0.928	-1.047***
	(0.786)	(0.380)	(0.779)	(0.390)
Interacted with *market* share	2.213	0.821	3.341***	0.0244
	(1.400)	(0.633)	(1.254)	(0.932)
newvlag		3.785***		3.792***
		(0.0935)		(0.0885)
MEs (%): *System* share	33.6***	33.6***	31.4***	34.0***
(baseline)	(3.03)	(2.10)	(2.93)	(2.32)
MEs (%): *System* share	-0.848	-1.26***	0.693	-0.831***
(extra)	(0.564)	(0.312)	(0.582)	(0.310)
MEs (%): *Market* share	4.25	9.41***	2.15	10.2***
(baseline)	(3.36)	(1.88)	(3.60)	(2.90)
MEs (%): *Market* share	1.59	0.673	2.50***	0.0194
(extra)	(1.00)	(0.519)	(0.937)	(0.740)
N	19,175	691,44	18,018	71,268
Pseudo R^2	0.651	0.864	0.638	0.872
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$	0.00489	6.01e-12	0.00624	3.39e-15

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Other regressors include the moderator variable, the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors (based on 50 replications) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 1 More about industry background

More about the organization structure of hospital chains

According to the American Hospital Association (AHA), a hospital chain/system is defined as "either a multi-hospital or a diversified single-hospital system." In other words, it could consist of multiple hospitals (in which case, it is not necessarily vertical integration) or include both hospitals and affiliated healthcare organizations that provide non-hospital care services, a case similar to vertical integration.[29] Note that the organizations that offer non-hospital care are generally pre- and post-acute healthcare organizations that provide supplementary services to hospital (usually acute) care.

More often than not, affiliated hospitals (and affiliated non-hospital facilities) are managed by a central organization. The organization structure of a hospital chain could be rather complex and varies substantially by chain. Even though no dominant organization structure exists, some common elements do: the board of trustees/directors that governs the entire organization; hospital administration, which includes different levels of managers; medical staff including physicians and nurses who provide medical services; and so on.

Health IT involves the storage, retrieval, and sharing of patient data that can be used in communication and health care decision-making. Given its disruptive nature and multidimensional impacts, the investment on it imposes non-trivial changes to the entire organization and has become part of the strategic planning at the organization level (Vassolo et al., 2021), the decision for which usually involves the top level of decision-makers, namely, the board and the executive team.

[29] See Fast Facts Archive 2019 from the AHA Annual Survey: http://www.aha.org/research/rc/stat-studies/fast-facts.shtml.

However, the traditional "parent holding company model" is no longer the best practice for hospital chains, given the dramatic changes in the healthcare sector, including the recent wave of consolidation, the shift of a significant portion of acute care business from the inpatient to outpatient settings, the stronger ties to local communities, and the rapid application of advancing information technology and data analytics. In fact, the board structure for hospital chains could depend on the size of the system, the location/geographic spread of the system, the level of diversity of the patient population, and so on (Murphy et al., 2015). Some large hospital chains even have multiple boards across the system, including the corporate parent board and subsidiary (local) boards.

There is no consensus on the appropriate level of control and authority of the parent board over its affiliates, but the best practice seems to encourage the governance structure to leave room for local sites to make decisions regarding competition and asset investment. Similar to the decision-making of IT purchases among firms in the manufacturing sector, the question of what the optimal allocation of decision rights is within an organizational hierarchy has no simple solution (McElheran, 2014).

Core business of leading EMR vendors in this paper

The EMRs used by hospitals—inpatient EMRs—are different from the EMRs used in other settings, such as ambulatory EMRs that are used by physician offices. Inpatient EMRs are specialized for the hospital environment, encompassing a collection of various departments including radiology, pharmacy, labs, and so on. Thus, an integrated EMR within a hospital—the focus of this paper—is a hub that gathers all the patient data and can be linked to each department to streamline the storage and management of the patients' health information. The ambulatory EMRs are applied

to the ambulatory health care environment, which has no in-house lab or radiology department, but the records in an ambulatory EMR need to be easily portable or accessible, with more focus on the patient-centric features, such as patient reminders, electronic prescribing to outside pharmacies, broader access to build-as-you-go clinical summaries, and so on.[30]

The leading vendors in my study all specialize in inpatient EMRs, although some of them also sell EMRs to healthcare organizations that are not hospitals, such as physician offices, or are involved in other businesses in addition to health IT. For instance, Cerner, Epic, McKessons, Siemens, and Meditech are among the top-ranked vendors by physician practices (Black Book Research, 2015). Moreover, some vendors engage in a wide arrange of health-related business. For instance, besides inpatient EMR products, GE healthcare also offers physician groups IT solutions on cardiology and radiology, diagnosis assisting applications enhanced by the artificial intelligence technology, and so on.[31]

Information on other businesses at the market level may be an indicator of vendor market attractiveness. The HIMSS Analytic database contains adoption information on both the ambulatory EMRs and inpatient EMRs. In particular, for the former, the dataset records adoption information for ambulatory/subacute care facilities *affiliated* with hospitals. Although the market penetration of ambulatory EMRs could suggest vendor popularity in the local area to some extent, it might not work for all the vendors considered in this study, because some of the leading vendors do not have businesses specializing in ambulatory EMRs. Also, since the data are only available for affiliated non-hospital care facilities, the choice of these facilities might be endogeneous, that is, affected by the affiliated hospitals.

[30]See https://www.practicefusion.com/blog/emrs-hospital-vs-ambulatory-solutions/.
[31]See https://www.gehealthcare.com/products/healthcare-it.

My paper focuses on inpatient EMRs. I use only the inpatient components in the the HIMSS Analytic database for my study. The list of the leading vendors in my study is generally consistent with the ones documented by the popular press (Black Book Research, 2014) and other studies. For instance, Holmgren et al. (2018) examine the relationship between hospital performance and the chosen vendor and share a list of major vendors similar to my study.

The HIMSS analytic database also provides product information for each EMR component of each vendor. I collected all the product information during my sample period, searched the internet, and summarize the information in Appendix Table A2. To sum up, most of the leading vendors, except McKessons and Meditech, include a unified "suite" for the integrated EMR system that gathers various components/functionalities together. McKesson included two different platforms, each targeting hospitals of different sizes, and decided to focus on one of them since 2011. For Meditech, the two platforms are based on the same programming language. As a result, I find that the EMR systems supplied by leading vendors are mainly built on a single platform.

However, a vendor usually offers multiple products with different features that allow customized implementation, and most of the associated products serve different purposes in health information management. They are either integrated into the "suite" or share similar programming language with the "suite." The provision of these products could lead to heterogeneity between hospitals choosing the same vendor, and thus, two hospitals being on the same vendor platform does not necessarily imply both are interoperable with each other.

Mergers and acquisitions between EMR vendors

During the study period, one merger occurred among the leading vendors I focus on. Specifically, Eclipsys (the leading vendor) merged with Allscript (a non-leading vendor in my study) at the end of 2010.[32] In my analysis, I let Eclipsys "exist" during the whole sample period, even after 2010. I replace Allscript with Eclipsys for hospitals that had Eclipsys in place in 2010 and for which the vendor in record became Allscript starting in 2011. However, if the vendor in record became any other vendor but Allscript in 2011, I make no changes for that hospital. For instance, consider a hospital that first adopted Eclipsys in 2007, remained working with this vendor until 2010, and switched to Epic in 2011. Then, the vendor in record for this hospital would be Eclipsys from 2007 to 2010 and Epic from 2011 until the end of the sample.

Treating the merger and acquisition activities in this way could face two limitations. First, including Eclipsys in the analysis during the post-merger period implies that this vendor was still available after it was acquired, which might lead to model misspecification. I conduct a sensitivity test by running the main regressions on a shorter period, from 2006 to 2010, when no merger and acquisition activities occurred among the leading vendors. The results are reported in Appendix Table A9. The main findings hold, which could help alleviate this concern. Second, I do not consider the mergers and acquisitions between fringe vendors—those grouped into the "others" category—in the analysis. However, given the relatively small market share of those vendors, I expect the bias in the results to be limited.

[32] See https://www.healthcareitnews.com/news/allscripts-eclipsys-merge-13-billion-deal.

Entry and exits of EMR vendors

The leading vendors considered in the main analysis entered the market well before the beginning of the sample period and had been in the market during the entire sample period, except for the merger and acquisition activities mentioned above. These facts can be observed in the HIMSS analytics database. In fact, the HIMSS dataset includes information on adoption status and vendor records even before 2000, and all the leading vendors existed during that period.

My study focuses on the period after 2005 for the following reasons. Hospitals often engaged in different adoption and management strategies on health IT in earlier years (well before the mid 2000s). There were two main implementation strategies: the best-of-breed approach, in which hospitals procure the technology to serve the needs of a specific unit or specialty; and the single-vendor approach, in which most/all health IT applications within the organization are purchased from the same vendor. Hospitals initially adopted the best-of-breed EMRs in the key specialty areas, such as emergency departments and anesthesia, and more often than not, each individual application is a stand-alone system, coming from a different vendor (Hermann, 2010). Over time, these applications grew exponentially, making coordinating multiple systems difficult and costly for hospitals. Also, the increasing emphasis on healthcare quality in law and regulations further stimulated the demand for an integrated and centralized system. Starting in the mid 2000s, the single-vendor approach saw a significant increase in market demand.[33] Studies have found that by 2007, the majority of hospitals chose the single-vendor strategy in EMR adoption (Ford et al., 2010). As a result, using data after the mid 2000s ensures hospitals are pursuing the single-vendor

[33]See https://blog.thesullivangroup.com/the-history-of-emrs-opportunities-to-improve-patient-safety.

approach, which is important given the goal of this study.

Competition concerns in choosing EMR vendors

Choosing the same vendor as neighboring hospitals may not be beneficial, due to competition concerns. When data transmission becomes relatively easy, hospitals may worry about losing patients, especially those with insurance plans that set less stringent rules for referral.

Patients know that their medical records need to be transferred between hospitals if they are going to leave the current hospital, even before deciding which one to switch to. However, how to send the records to the new hospital are usually unknown until the choice is made, because the ways to transfer the information vary, depending on the specific healthcare providers.[34] For instance, if the old and new hospitals have interoperable health IT systems, the transfer process tends to be easy without much involvement from the patient. However, one might have to rely on fax machines or physical delivery of medical records if one of the hospitals does not have a well-established EMR system. Moreover, it might incur additional financial costs, because in some states, patients have to pay a certain fees to have the records transmitted (Baker et al., 2015). The resulting costs of the data transfer—including the time, efforts, and expenses—might play a role in the final decision of switching hospitals, especially among the marginal patients. Nevertheless, as regulations tend to make the extraction of medical records easier for patients and patients who indeed switch hospitals usually have a substantial reason to do so, the costs of sending health information, overall, might not play an important role in patients' decisions about where to seek care. This reason could explain why related studies have not found significant evidence of the

[34] See https://www.forbes.com/sites/christinalamontagne/2015/04/29/how-do-i-get-my-medical-records-transferred/?sh=9beef5871c82.

competition effect.

To test the hypothesis that choosing the same vendor with local providers may not be beneficial to hospitals due to competition concerns, I use the median HHI as the cutoff and divide the markets in the IV sample into two groups: competitive and concentrated markets. I rerun the main (IV) specification separately on each type of markets. Table A13 shows the results. Both new and experienced adopters seem to value external popular vendors to a greater extent in competitive markets than they do in concentrated markets.

Complementarities could play a role here. Network benefits, both internal and external, can arise from (1) cost savings in implementation and operation that could be due to increasing returns to scale or (2) potential efficiency gains in information transfer with other (affiliated or non-affiliated) healthcare providers. The result that the profitability of external network effects increases with competition might suggest that cost savings have an important impact on how a hospital evaluates a vendor's local prevalence. Choosing the local popular vendor could reduce implementation costs, because such a vendor can achieve economies of scale by providing similar resources and services, which could translate into a cost advantage. For instance, hospitals need to install interfaces to connect to other disparate information systems. Developing an interface for a popular system may take only one third the cost of that for a lesser known or discontinued system.[35] Given that the implementation of EMRs is very expensive, hospitals would have greater incentives to choose the dominant local vendor for cost savings in a more competitive market, holding other things constant.

[35] See https://www.healthitoutcomes.com/doc/how-much-will-an-ehr-system-cost-you-0001.

Appendix 2 A simple theoretical model for adoption decision

I develop a simple model characterizing the choice of EMR vendors for affiliated hospitals. There are M regional markets, each of which has N_m affiliated hospitals, $\forall m = 1, 2, ..., M$. These affiliated hospitals are associated with Q hospital systems, and each contains N_q members, $\forall q = 1, 2, ..., Q$. To maximize the ex-ante profit, every hospital *simultaneously* decides whether to adopt EMRs and, if yes, chooses a vendor j from the set $\mathcal{J} = \{1, 2, ..., J\}$. Given that most of the vendors serve the national market, I assume that $\mathcal{J}$ is fixed for every hospital. Note that not all vendors are likely to be equally accessible to every hospital/chain. I make the assumption for simplicity and also considering a recent trend that vendors are seeking a wide variety of customers. For instance, certain vendors that used to target large hospitals start to approach small or community hospitals.[36] However, in cases where only a subset of vendors is available in certain locations or to certain hospitals/chains, my model does not distinguish between a vendor being unavailable or not being chosen, which could be a potential limitation.

Specifically, a hospital that has no EMRs either purchases from vendor j or remains with no IT system. A hospital with an on-site system either continues with the current choice or switches to a different vendor, but reversion to non-adoption is not allowed.[37] I assume that each hospital has the same margin between price and marginal cost and thus captures a fixed portion of consumer surplus. As a result, oligopoly competition in medical care is not be explicitly considered in the

[36] See https://www.healthcareitnews.com/news/now-epic-goes-small.

[37] A conversation with industry experts suggests that reversion is almost impossible. The raw data show less than 1% reversion, and most of these hospitals either "restored" to adoption or were recorded with a different vendor the next year. The reversion in data is possibly due to input error or because of the fact that the hospital was in the middle of transition to a new system. Therefore, I assume that, in this case, the hospital maintains the same record as last year in the empirical analysis.

model.[38] I further assume that each decision period is one year.

Let hospital i's profit from adopting vendor j at time t, π_{it}^{j}, have the following form:

$$\pi_{it}^{j} = X_{it-1}^{j}\alpha + W_{it-1}\gamma^{j} + \mathcal{M}_{it-1}^{j} + \varepsilon_{it}^{j}, \tag{3}$$

where X_{it-1}^{j}, W_{it-1}, and $\mathcal{M}_{it-1}$ denote the lagged vendor, hospital, and market characteristics, respectively. Let

$$\begin{aligned} X_{it}^{j}\alpha = {} & \text{MktShare}_{it}^{j}\alpha_{\text{mkt}} + \text{SysShare}_{it}^{j}\alpha_{\text{sys}} + \sum_{\ell\in\mathcal{J}}\left[\mathbb{1}\{\ell = j\}(\alpha_{\ell} + \varphi_{\ell}\times t)\right] \\ & + \mathbb{1}\left\{i \text{ has EMRs}\right\} \times \mathbb{1}\left\{j \text{ was chosen at } (t-1)\right\}\alpha_{\text{chosen}}, \end{aligned} \tag{4}$$

where MktShare_{it}^{j} and SysShare_{it}^{j} denote the share variables. The local *market share* is defined as the ratio of the total number of local hospitals adopting vendor j to the total number of hospital adopters in the local market. The *system share* is defined as the fraction of affiliated hospitals adopting this vendor among all member hospitals with EMRs. I exclude the focal hospital in constructing the share variables. I also try using the weighted average of shares that accounts for the number of beds in the empirical analysis. The main results hold. Appendix 4 provides more detail. The third term on the right-hand side incorporates vendor fixed effects and vendor-specific time trends, with the former controlling for other unobserved vendor characteristics[39] and the latter capturing the overall changes in vendor quality/promotion/popularity over time.[40] For hospitals

[38] I acknowledge that it is a restrictive assumption, but prior empirical studies that examine network effects make a similar assumption (Gowrisankaran and Stavins, 2004; Desai, 2016; Wang, 2021).

[39] Such characteristics include IT capabilities at the vendor level, namely, system quality, usability, functionality, technical support, and others.

[40] An arguably better way is to include vendor-year fixed effects to allow for unrestricted, differential trends by

with EMRs, to evaluate the extent to which a hospital sticks to the chosen vendor, I further include an indicator for whether a particular vendor was previously chosen.

I let W_{it} represent variables that are constant across vendors but vary by hospital, such as hospital-specific features. $\mathcal{M}_{it}^{j}$ denotes the profit associated with market characteristics, namely, those related to healthcare competition and affecting hospital adoption decisions at the same time. ε_{it}^{j} denotes profit shocks that are unobservable to econometricians. Let a_{it} denote the adoption choice by hospital i at time t. Thus, hospital i will pick vendor k, that is, $a_{it} = k$, if $\pi_{it}^{k} \geq \pi_{it}^{j}$, $\forall j \in \mathcal{J} \setminus \{k\}$. Let δ_{it}^{k} denote the mean profit from choosing vendor k at time t; that is,

$$\delta_{it}^{k} = X_{it-1}^{k}\alpha + W_{it-1}\gamma^{k} + \mathcal{M}_{it-1}^{k}. \tag{5}$$

The profit from non-adoption is normalized to zero. I assume that ε follows the Type I extreme value distribution. Therefore, the probability of hospital i, without EMRs, choosing vendor k has the following form:

$$\text{Prob}(a_{it} = k) = \frac{\exp(\delta_{it}^{k})}{\sum_{j \in \mathcal{J} \cup \{0\}} \exp(\delta_{it}^{j})}. \tag{6}$$

By the same logic, I can write down the probability for hospital i that has already adopted EMRs choosing vendor k:

$$\text{Prob}(a_{it} = k) = \frac{\exp(\delta_{it}^{k})}{\sum_{j \in \mathcal{J}} \exp(\delta_{it}^{j})}. \tag{7}$$

Several points are worth noting. In the current setting, the estimated network benefits may stem from the correlation between the non-adoption within the system/market and the non-adoption of the focal hospital. To examine this, in the empirical analysis, I re-estimate the main specification

vendor, but doing so would result in many more parameters and make the estimation less precise.

based on the sample including only hospital-year observations with adoption/switching decisions, excluding the option of the current choice. This specification provides an estimate of the correlation between the probability of choosing a vendor and its system/market share, conditional on adoption/switching. I report the results in Appendix Table A10. The findings are qualitatively similar to the main results in Table 4.

Moreover, due to data constraints (e.g., lacking information on price or contract value), I construct the model from the perspective of hospitals—the demand side of the market—assuming that hospitals take as given what is offered/has occurred on the supply side. However, the adoption choice is likely to be an outcome from the interaction—such as negotiation—between the hospital/chain and the vendor. I acknowledge such a setup is a limitation. To minimize the effect of such interactions at the market (chain) level so that α_{mkt} (α_{sys}) *only* reflects the external (internal) network benefits, I use IVs in the empirical analysis and provide more detail in the section on empirical strategy. In addition, I use a static model, considering that the choice of brands might require less dynamic optimization than the fundamental decision to acquire an EMR system. Finally, following the literature on EMR adoption built on network effects theory, I use a vendor's popularity in the local market and parent system as primary determinants in the profit from adoption, given the focus of this paper. The effects from other IT capabilities that might be important in vendor selection decisions will be captured in the fixed effects or other control variables.[41] Prior studies apply a similar approach in modeling technology adoption with network effects (Gowrisankaran and Stavins, 2004; Desai, 2016).

[41]The capabilities may include functionality, quality, usability, add-on applications, and value-added services in terms of training, support, and customization.

Appendix 3 More discussion on endogeneity and IVs

More detail on IVs

I provide more detail on how to construct IVs for the two share variables and discuss the exclusion restriction assumption here.

IVs for market share

Consider an example of hospital A_1, a member of chain $\mathbb{A}$ located in market m_1, as shown in Appendix Figure A8. I call the market where the focal hospital (A_1) is located, m_1, the *focal market*. The endogenous variable for A_1 is a vector with each entry indicating the market share for the corresponding vendor in m_1. Suppose that B_1 is affiliated with chain $\mathbb{B}$, the rest of whose members, $\{B_2, B_3, B_4, B_5\}$, are equally distributed in m_2 and m_3. I call $\mathbb{B}$ an *associated chain*, because it has member hospitals in the same market as the focal chain, $\mathbb{A}$. The instruments for A_1 are the average of the market dominance indicator and market share for each vendor across m_2 and m_3—the outside associated markets. This instrument is relevant in the sense that the managing party of $\mathbb{B}$ may take into account the market conditions in m_2 and m_3, which will affect the choice by B_1 and ultimately A_1. It is a clean measure because these outside markets plausibly have little relation to the unobservables in m_1.

The exclusion restriction in this instrument boils down to vendor market share in the outside associated markets only affecting the focal hospital's vendor choice via its effect on the local vendor market share. In other words, no spillovers in unobservables occur between the focal market, m_1, and the outside associated markets, m_2 and m_3. A threat to identification could occur

if a vendor offers market-wise promotion or establishes a large-scale sales network in m_1, m_2, and m_3 at the same time, because all the members of $\mathbb{B}$ are located in these markets. To assuage these concerns, I base the IV analysis on the sample satisfying the following conditions. First, I focus on the focal markets that are treated as "unimportant" in the overall decision-making of the associated chain, such as m_1 for $\mathbb{B}$.[42] I view a market as "important" for a hospital chain if, among all the markets where the chain is located, this market includes most of its members (e.g., m_2 and m_3 for $\mathbb{B}$), and as "unimportant" otherwise (e.g., m_1 for $\mathbb{B}$). I construct the instruments using markets that are likely to play an important role in the decision process for the associated chain, such as m_2 and m_3 for $\mathbb{B}$. By doing so, I reduce the likelihood that affiliated hospitals in the outside associated markets respond to the variations in the focal market. Moreover, the exclusion restriction also requires that this instrument is conditional mean independent of the unobservables at the system level. I further remove an outside associated market if it plays a significant role for the focal chain.[43] Finally, to avoid spillovers across markets due to proximity, I only keep outside associated markets that are at least 180 miles away from the focal hospital.

Appendix Figure A6 shows an example of a focal hospital and its outside associated markets in the actual data. The focal hospital is located in Florida, for which the three outside associated markets are located in Mississippi, New York, and Pennsylvania.

[42]Including only the "unimportant" markets could lead to a sample selection problem, because market participation or coverage by chains could be endogenous; hospital chains tend to enter the most profitable or largest markets. I also redo the main analysis using both important and unimportant markets for the associated chains. The main findings hold, as reported in Columns (3) and (4) of Appendix Table A11. Note that the similarity between the two sets of results are probably due to the similar number of observations between the two specifications. The number of hospitals increases by less than 20% if important markets are included in the IV sample. The increase in the IV sample is even smaller because not all the hospitals in these markets have IVs for system share and will not be included in the IV analysis.

[43]The focal chain will likely choose a vendor that offers market-wise promotions in the important markets. Including it will result in endogeneity for the system share variable.

IV for system share

I construct the instrument for the system share variable based on *associated chains*, namely, those sharing common markets with the focal chain. Specifically, I first identify all associated chains given a focal chain, and then calculate the average of the system share and system dominance indicator for each vendor across these chains. For instance, in Appendix Figure A9, both $\mathbb{A}$ and $\mathbb{B}$ are hospital chains. Moreover, $\mathbb{B}$ is an associated chain for $\mathbb{A}$. The proposed IVs satisfy the relevance condition, because the adoption choice of all members in $\mathbb{B}$ will affect the choice of B_4 and hence A_2 and, ultimately, the system share for $\mathbb{A}$. $\mathbb{B}$ is exogenous to $\mathbb{A}$ in that the interaction between $\mathbb{B}$ and its chosen vendors is plausibly private and thus will be independent of that between $\mathbb{A}$ and its vendors.

However, concerns may exist regarding unobserved spillovers via the shared markets. I construct the instruments from a subsample that meets the following criteria. First, I keep an associated chain if none of its important markets are important for the focal chain, such as $\mathbb{B}$ for $\mathbb{A}$ in Figure A9. As a result, $\mathbb{B}$ places much less weight on the markets that are important to $\mathbb{A}$. Second, I construct the instruments based on chains whose average distance to the focal chain is at least 180 miles.

Appendix Figure A7 presents an example of a focal chain and its associated chains from the data. The focal chain has two important markets: one on the northwest coast (shown in the left subfigure) and the other on the southwest coast (shown in the right subfigure), with the latter containing hospitals from the associated chains that are widely spread out in the rest of the country. Note that the important market for the focal chain that is located on the southwest coast is unimportant for all the associated chains.

l use the CF approach because of the nonlinear relationship. The first step is to respectively regress the endogenous variables—market share and system share—on the instruments and the exogenous variables described above. The regression equation has the following form:

$$Y_{ijt} = Z_{it}^{j}\beta^{Z} + \sum_{\ell \in \mathcal{J}} \left[\mathbb{1}\{\ell = j\}(W_{it}\beta_{\ell}^{W} + \mathcal{M}_{it}^{\ell} + \alpha_{\ell} + \varphi_{\ell} \times t) \right] + e_{ijt}^{Y}, \tag{8}$$

where Y_{ijt} denotes the market or system share; Z_{it} denotes the corresponding instruments; other variables are defined as in Equations (1) and (2); and the β's are the corresponding coefficients. I obtain the error terms, $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$, respectively, from each of the equations. Next, I obtain the parameters by maximizing the probability of the observed data, with the probability of each observation equal to the following:

$$\text{Prob}\left(D_{it}^{j} = 1 \middle| X_{it-1}^{j}, W_{it-1}, \mathcal{M}_{it-1}\right) = \frac{\exp\left(X_{it-1}^{j}\alpha + W_{it-1}\gamma^{j} + \mathcal{M}_{it-1}^{j} + f(\hat{e}_{ijt}^{\text{mkt}},\, \hat{e}_{ijt}^{\text{sys}})\right)}{1 + \sum_{k \in \mathcal{J}} \exp\left(X_{it-1}^{k}\alpha + W_{it-1}\gamma^{k} + \mathcal{M}_{it-1}^{k} + f(\hat{e}_{ikt}^{\text{mkt}},\, \hat{e}_{ikt}^{\text{sys}})\right)}, \tag{9}$$

where

$$f(\hat{e}_{ijt}^{\text{mkt}},\, \hat{e}_{ijt}^{\text{sys}}) = \hat{e}_{ijt}^{\text{mkt}} + (\hat{e}_{ijt}^{\text{mkt}})^{2} + \hat{e}_{ijt}^{\text{sys}} + (\hat{e}_{ijt}^{\text{sys}})^{2} + \hat{e}_{ijt}^{\text{mkt}}\hat{e}_{ijt}^{\text{sys}}.$$

Note that the consistency results for the CF estimation only guarantee that some function of the first-stage residuals will make the second stage produce unbiased estimate. Thus, I include the first-stage residuals with a polynomial expansion in the second stage.[44] I obtained the standard

[44]The results using expansions with higher degrees are similar.

errors by bootstrapping to account for the estimation error in the first stage.

Appendix Tables A3 and A4 summarize the key statistics for the IV sample. On average, each new (experienced) adopter corresponds to approximately 3 to 4 (3 to 4) outside associated markets and 5 to 7 (7 to10) associated chains. Also, hospitals in the IV sample are less likely to be teaching or not-for-profit hospitals. Both the chains and markets are larger than those in the overall sample, as shown in Appendix Tables A3 and A4. The implications from the IV analysis mainly apply to these hospitals/chains/markets.

Endogeneity due to simultaneity

The market share variable may also suffer from endogeneity due to simultaneity. The simultaneity bias arises because the choice probability of a particular vendor and the vendor's local market share can be determined simultaneously, due to the unobserved price and quality. To better understand how endogeneity is driven by simultaneity, consider price as the only unobserved variable for simplicity, and the simultaneity due to unobserved quality follows a similar logic. Suppose a vendor implements the following pricing strategy for the focal hospital: low (fixed) installation costs and high (variable) maintenance costs. Both the choice of vendor (the dependent variable in the analysis) and the vendor's local market share (the key variable of interest) depend on the vendor's price. Moreover, the pricing strategy of this vendor could depend on the hospital's demand for this vendor (and maybe the local market demand for its product as well). As a result, the variables on the left- and right-hand sides are jointly determined. Omitting price from the estimation can drive simultaneity bias on the coefficient for the key variable of interest—the local market share.

The simultaneity bias might not be substantial since I use the lagged market share as the key

variable of interest. Also, the IVs for market share in the main analysis have the potential to address this bias. Recall the IVs used in the paper: the market share and market-dominance indicator in the focal hospital's outside associated markets. These instruments are exogenous to price for the following two reasons. First, a vendor could implement different pricing strategies for different hospitals, and thus, the market share of a given vendor might represent an outcome from a "synthesis" of various pricing strategies for different local hospitals. Second, the IVs reflect the relative position of the vendor in the external markets. A not-that-crazy assumption is that the vendor's "synthesized" pricing strategy for a market is highly correlated with the market competitiveness of EMRs. For instance, the "synthesized" strategy is close to the non-linear pricing strategy mentioned above (low fixed installation costs and high variable maintenance costs) in a very competitive market. If the level of competitiveness is different between the focal market and the outside associated market, the pricing strategy for the focal hospital could, on average, be plausibly different from the "synthesized" strategy for the outside associated market. Based on this assumption, I refine the current IV analysis by further excluding the outside associated markets that share a similar level of competitiveness to the focal market, so as to reduce the simultaneity bias. Columns (1) and (2) of Appendix Table A11 show the results based on the modified IV estimation, and the main findings hold.

A threat to identification is that a vendor adopts an across-the-board pricing strategy, that is, applying the same strategy for all customers. In this case, the market condition in outside associated markets could still be endogenous. However, implementing a uniform pricing strategy for a long time could be costly. My sample covers the period from the early stage to the relatively mature stage of EMR adoption. Vendors are more likely to consider the "lock-in" pricing strategy at the

early stage of the market. Finally, note that the discussion above is based on the assumption that decisions across periods are not serially correlated. If this assumption does not hold, the proposed IVs might not completely resolve the endogeneity issue arising from simultaneity with the lagged market share, which could be a limitation of the paper.

Endogeneity with HHI

The hospital HHI variable is likely to be endogenous, as there might be unobservables affecting the market structure and the choice of vendors at the same time. For instance, a hospital may select/unselect a certain type of vendors because of the population served, which might also affect the competition in the local market. As a result, I do not interpret the coefficient for HHI as a marginal effect but treat this variable as a control variable. I interpret the coefficients for the key variables of interest as the impacts after controlling for the local market structure of hospital care. The coefficients for the key variables of interest—α_{mkt} and α_{sys}—are unaffected by the potential endogeneity of HHI if the unobservables are not correlated with the instruments, after HHI is controlled. In other words, conditional on HHI, the residual in the main regression, ε_{it}^{j}, is mean independent of the instruments.

Endogeneity with the switching variable

I include in the model a switching variable—an indicator for whether a particular vendor was previously chosen—to control for hospitals' switching incentive. However, this variable could be endogenous due to the unobserved price or quality, and thus, the estimated coefficient might just reflect an association instead of a causal correlation. Besides, including this variable could also

bring in the initial conditions problem, a different mechanism that could raise concerns on endogeneity. In this case, it is uncertain whether the estimates for the key variables of interest remain unbiased in such a (dynamic) model. As a robustness check, I redo the IV analysis, excluding the switching variable, and present the results in Column (5) of Appendix Table A11. The effects from both share variables remain significantly positive, with a greater magnitude in the effect of market share than that in the main results. It suggests that the model might suffer from the initial conditions problem if the switching variable is included, but the resulting bias could be limited. The main finding remains: experienced adopters appreciate both the internal and external network benefits and place more value on the former.

Appendix 4 More discussion on the results

Mechanism: Need for internal coordination

In discussing this mechanism, I propose two competing propositions in the main text and find that the probability of hospitals following the parent system declines with the fraction of co-located, affiliated facilities that offer complementary services. This is consistent with the prediction that member hospitals that are relatively more important—such as those of relatively larger size or contributing relatively greater revenues to the entire chain—have more discretion in the level of external local adaptation (McElheran, 2014).

Prior studies have examined the correlation between the relative size or performance of a unit and the decision authority granted (McElheran, 2014; Sengul and Obloj, 2017). McElheran (2014) found that the unit contributing relatively high revenues tends to have more discretion on IT purchasing because the cost of mis-adaptation of that unit could be significant for the firm as a whole. Following McElheran (2014), I use the relative bed size of a member hospital—the ratio of the focal hospital's number of beds to the total number of hospital beds in the chain—as a moderating variable and present the results in Appendix Table A15. The findings are similar. The increase in probability, given the variation in system share, declines with the hospital's relative bed size, with a reduction of 5% ($= 1.65/33.0 \times 100\%$) in the average change of the probability among new adopters or 1.98% ($= 0.631/31.9 \times 100\%$) among experienced adopters.

Another force driving these results could be that vendors might have smaller market shares in markets with a larger number of healthcare providers or care facilities, due to more intense competition. To test this possibility, I regress a vendor's local market share on the total number

of healthcare providers (i.e., the sum of hospitals, ambulatory care facilities, and subacute care facilities) in each market, vendor system share, vendor fixed effects, market fixed effects, and year fixed effects. Moreover, I also replace the total number of healthcare providers with the EMR HHI, which is constructed by the market share of EMR vendors. Appendix Table A16 shows the results, suggesting that it could also be a possible explanation.

Finally, the results could also be related to the finding in McCullough et al. (2016) that hospitals benefit most from health IT adoption in treating severe patients that require substantial care coordination across healthcare providers and extensive clinical information management. Hospitals with a greater proportion of patients treated by multiple hospitals would benefit more from choosing a vendor that is widely adopted in the local market. This could explain why hospitals surrounded by many affiliated complementary facilities are less likely to choose the internally preferred vendor. Although I cannot verify this mechanism directly in the current study due to data limitation,[45] I examine it indirectly by using hospital case mix index (CMI) as a measure for the average patient complexity for each hospital.[46] The CMI is the average diagnosis-related group relative weight across all Medicare discharges in a hospital. Treating patients with complex, high-severity diagnoses may require cross-provider coordination and extensive information management. I use the CMI as a moderator variable and present the main results in Appendix Table A17. The interaction terms with CMI are statistically insignificant.[47]

[45]Datasets such as the Medicare Provider Analysis and Review (MEDPAR) or the limited data in the Healthcare Cost & Utilization Project could help examine this mechanism.

[46]I obtain the data from the Centers for Medicare & Medicaid Services Impact files. See https://www.nber.org/research/data/centers-medicare-medicaid-services-cms-casemix-file-hospital-ipps.

[47]Note that it does not refute the mechanism of external coordination for the following reasons. First, I use the CMI as a proxy for average patient complexity based on the assumption that the resources used to treat a patient are positively correlated with how complex the patient's conditions are. However, the value of CMI also depends on other factors, such as a hospital's documentation and coding practices. See https://journal.ahima.org/page/is-case-mix-index-still-a-relevant-key-performance-indicator. Second, a hospital's CMI may not

Additional robustness checks

I first test the sensitivity of the results in smaller vs. larger markets. Specifically, I divide the markets in the IV sample into two groups: small and large markets, using the median of the total population above 65 as the cutoff. I rerun the main specifications separately for each type of markets. Appendix Table A14 presents the results. It suggests that external network benefits produce no effects for new adopters and show a positive and significant impact on experienced adopters in large markets.

A potential explanation is that market size plays an important role in the value of external network benefits, especially among experienced adopters. Hospitals with existing EMRs have accumulated experience with the technology and have a better sense of what complementary resources are available nearby, and thus they are more likely to welcome outside options. In contrast, new adopters might rely on internal support and guidance from the parent system and thus are less likely to be affected by external factors. Also, as mentioned above, the external network benefits could arise from cost savings or potential efficiency gains in information transfer. In both mechanisms, the value of external network benefits could be potentially greater in larger markets: cost savings from choosing the local popular vendor increasing with market size due to economies of scale and the efficiency gains from information transfer increasing with market size due to a potentially larger network.

I also try alternative market definitions. First, I use hospital referral regions (HRRs), which are also commonly used to define geographic markets for healthcare services. Specifically, HRRs are delineated based on the referral patterns for highly-specialized care such as cardiovascular proce-

represent its overall demand for external coordination.

dures or neurosurgery and tend to be larger markets, with a minimum population size of 120,000.[48] Appendix Table A7 presents the main results based on this market definition. Compared with the results based on health service areas (HSAs), the main findings hold, except that new adopters seem to also favor external options in HRRs, as shown in Column (3). I chose HSAs over HRRs following related studies that examine the strategic interaction in the adoption decision of EMRs (Lin, 2021; Wang, 2021). Moreover, I view HSAs as a more appropriate market definition in my context, as HSAs are defined based on the provision of routine hospital care, whereas HRRs focus on highly-specialized care such as cardiovascular procedures or neurosurgery.

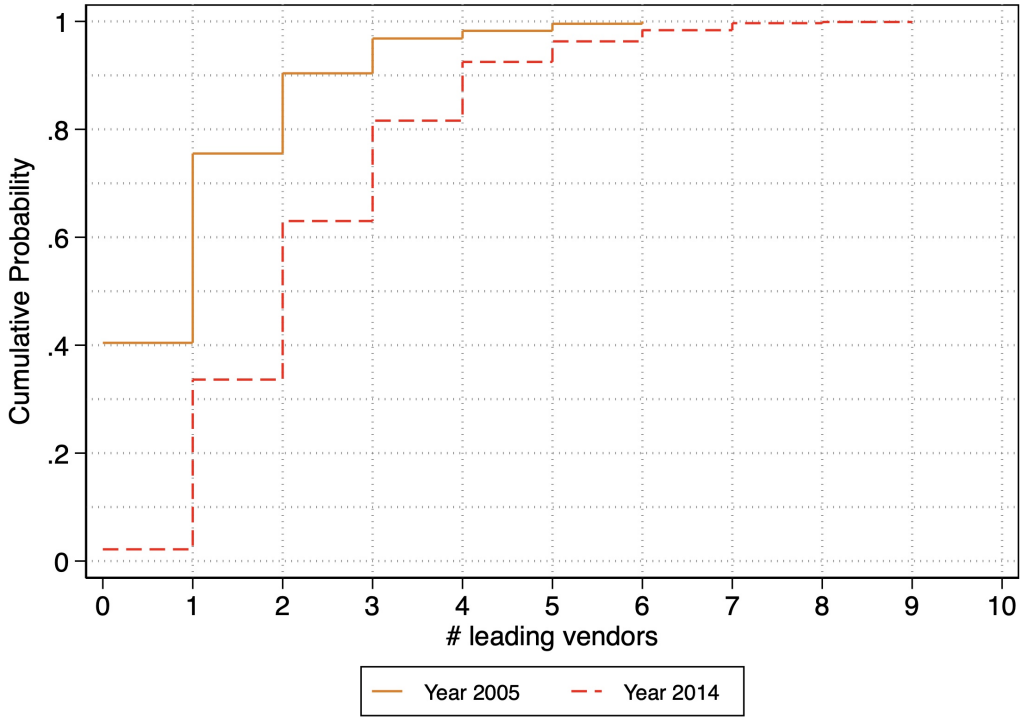
Second, following Lewis and Pflum (2017), I construct a market for each hospital based on a 45 mile radius, that is, all hospitals within a 45 mile radius of the focal hospital belonging to the same market. I calculate the distance between two hospitals based on the latitude and longitude of their zip codes. I also recalculate the market share and market-related control variables based on this definition. Appendix Table A8 reports the main results, and the main findings hold.

Finally, I use different specifications to conduct additional analyses to assessing the robustness of the main results. Appendix Table A12 presents the results deriving from five different specifications by progressively adding more controls and fixed effects for new and experienced adopters, respectively. The results are rather robust across different specifications among experienced adopters. For new adopters, the estimates for the share variables change substantially after vendor fixed effects are included in the specification, and the coefficient for market share becomes smaller as more control variables are included.

[48] See https://www.dartmouthatlas.org/faq/.

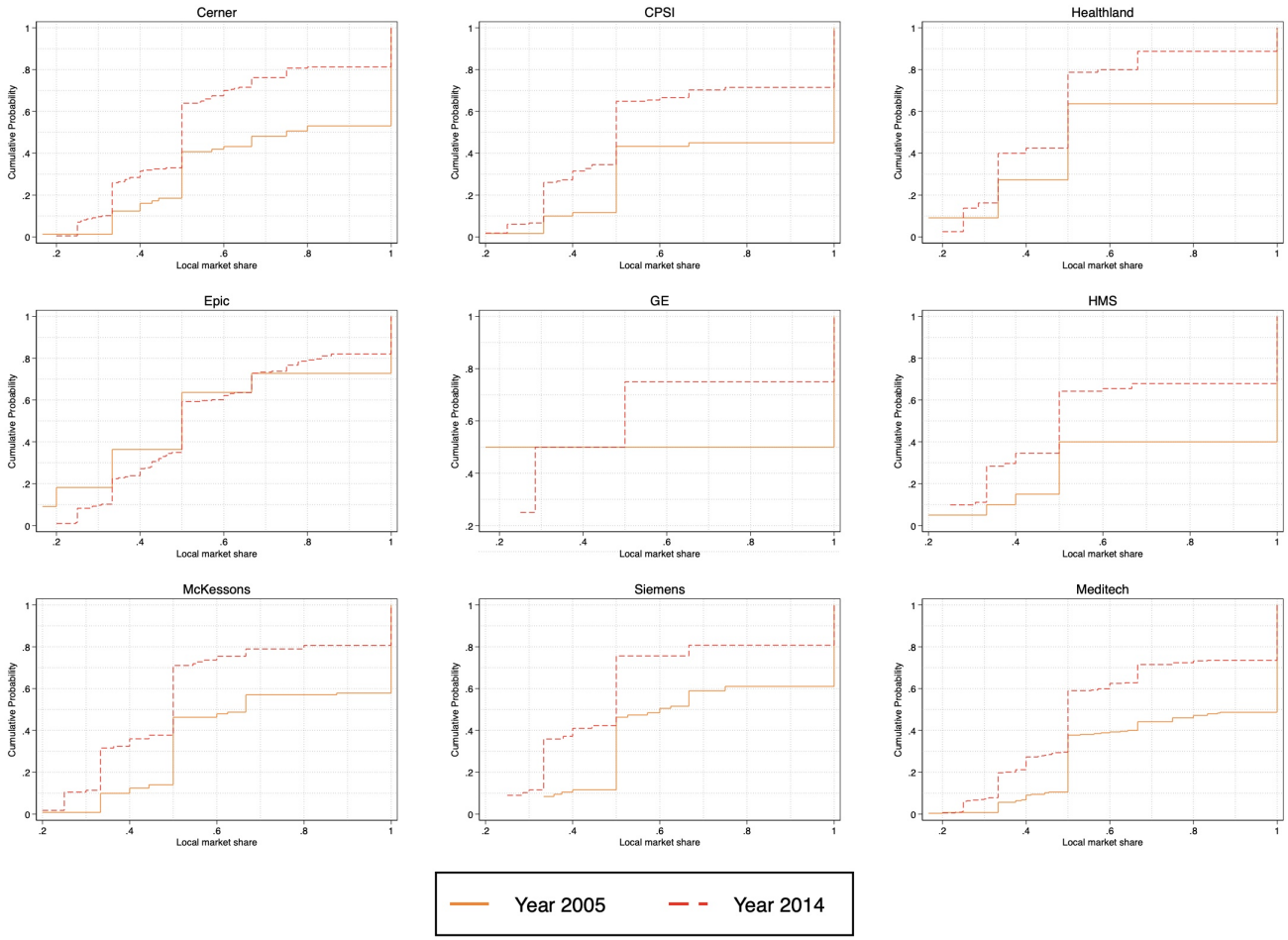
Appendix 5 Extra Figures and Tables

Figure A1: CDFs of number of leading vendors per market



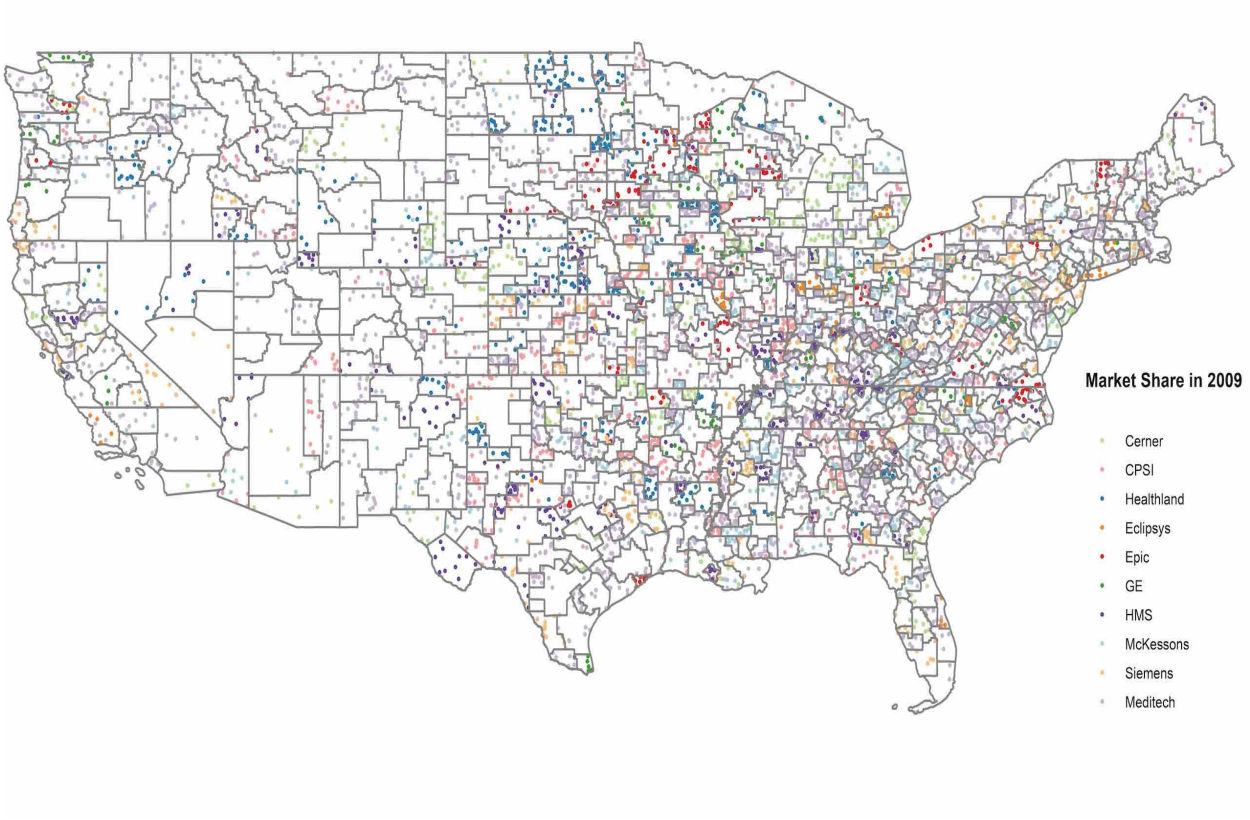
Note: Leading vendors per market taken from Appendix Table A1.

Figure A2: CDFs of market share for dominant local vendor



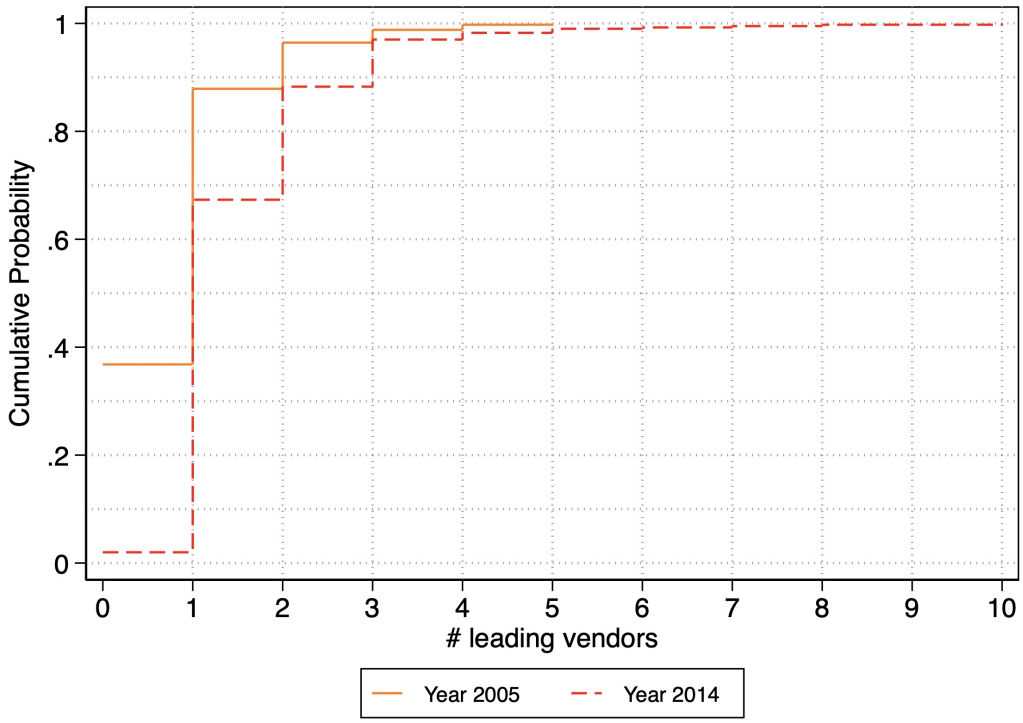
Note: Each panel shows the CDFs of a particular vendor's local market share among all the markets where this vendor is the local dominant vendor, that is, has the highest local market share.

Figure A3: Vendor distribution across markets in 2009



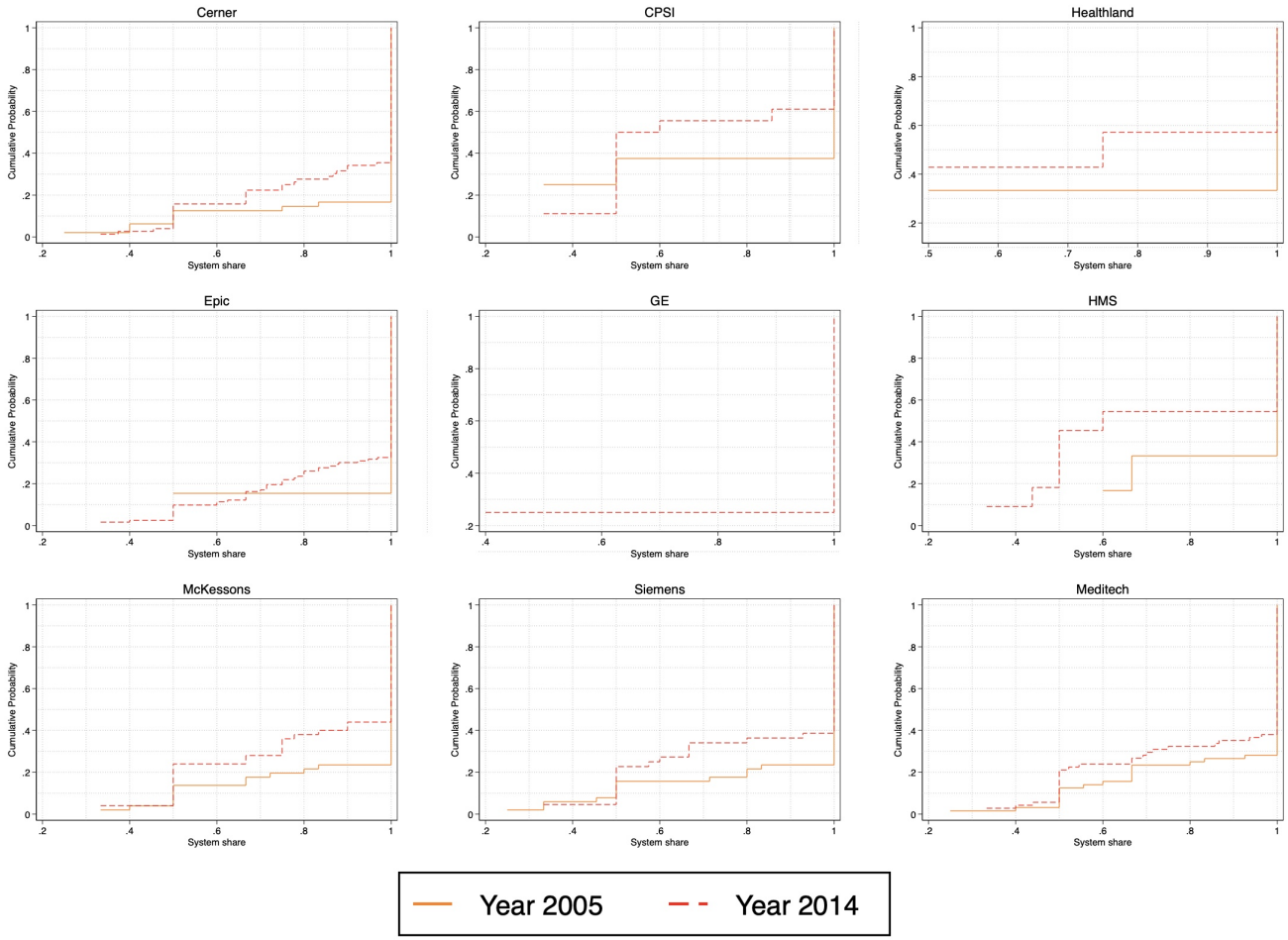
Note: Each patch represents a local market, and each color represents a particular vendor. Each dot stands for approximately 10% of local market share for the represented vendor. The clustering of dots of the same color within a market measures the extent to which the represented vendor dominates the local market. Note that the location of dots is randomly assigned by the software and does not pinpoint exact locations.

Figure A4: CDFs of number of leading vendors per chain



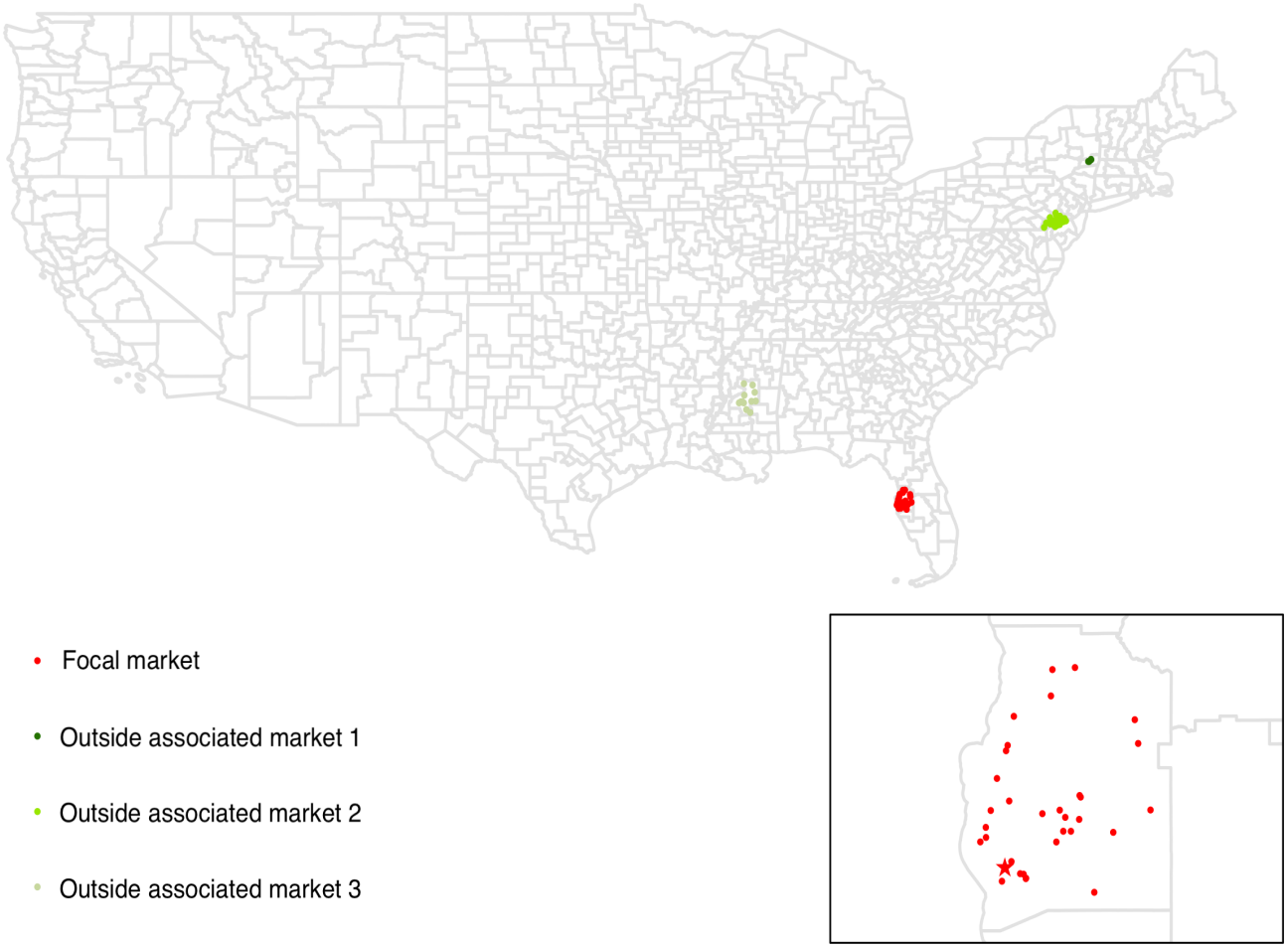
Note: Leading vendors per market taken from Appendix Table A1.

Figure A5: CDFs of system share for system-dominant vendor



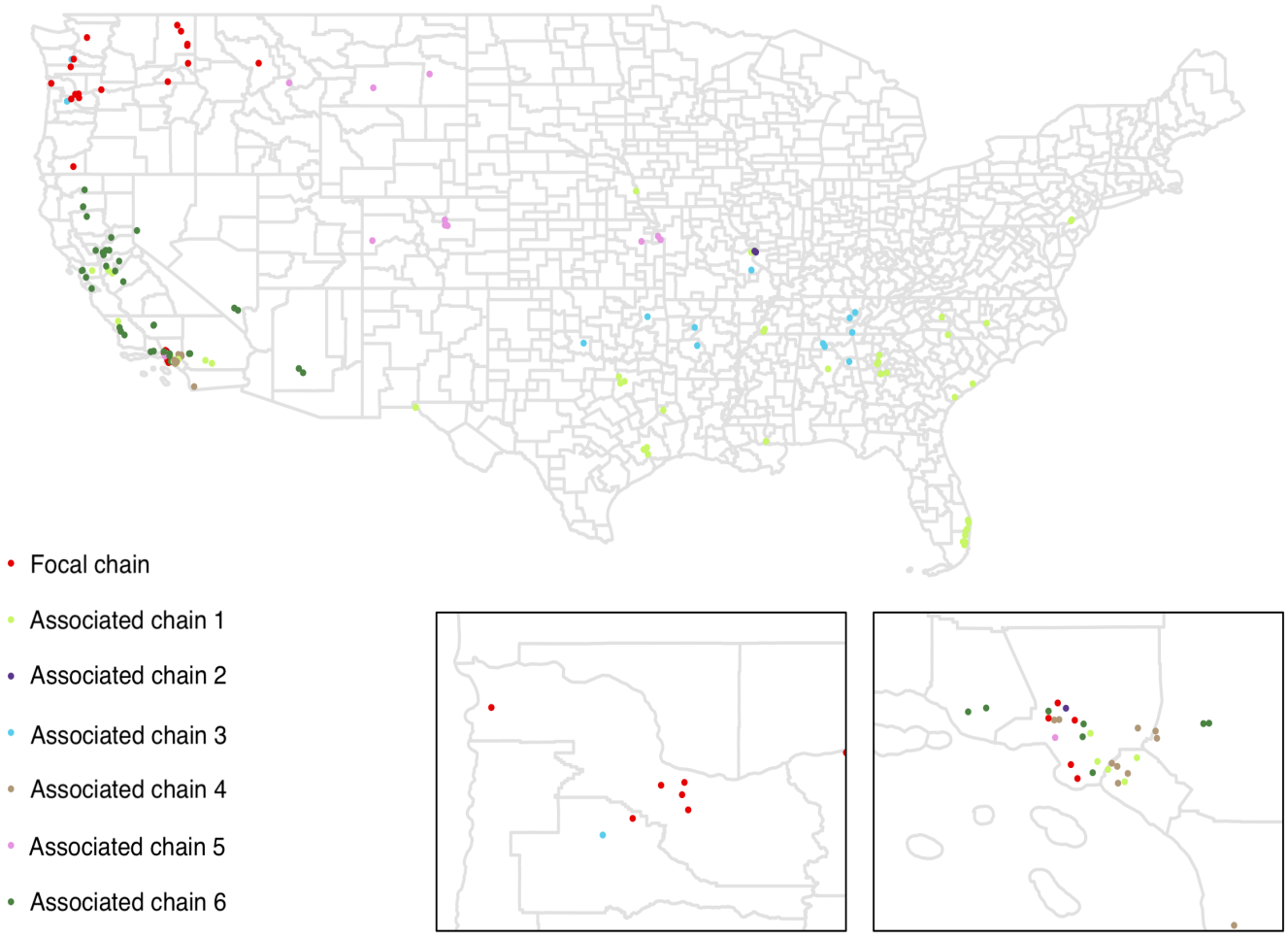
Note: Each panel shows the CDFs of a particular vendor's system share among all the systems where this vendor is the dominant vendor, that is, has the highest system share.

Figure A6: Example of outside associated markets in the data



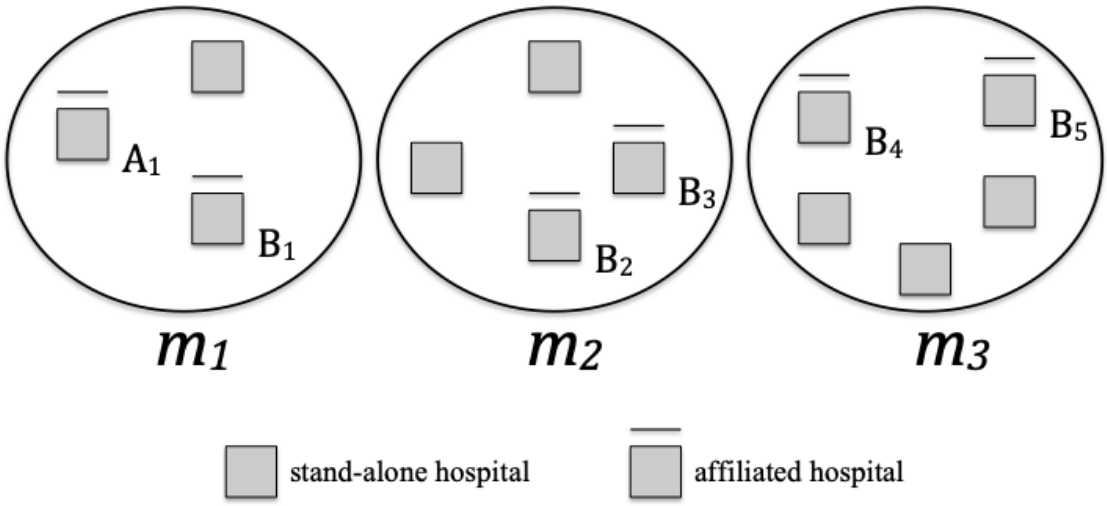
Note: Each patch represents a local market. The focal hospital is located in Florida, represented by a star in the subfigure. The subfigure shows the area after zooming in on the focal market in the map.

Figure A7: Example of associated chains in the data



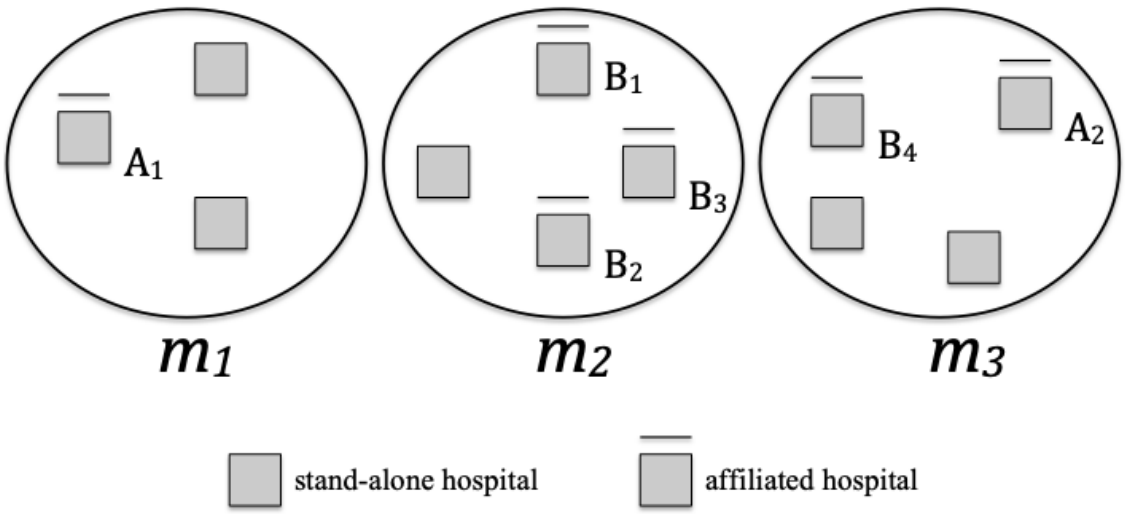
Note: Example of associated chains for a focal chain. Each subfigure represents an important market for the focal chain, with the right one showing the overlapped market that is important for the focal chain but small for the associated chains.

Figure A8: Example of how to construct instruments for market share



Note: Each square stands for a hospital. There are three markets: m_1, m_2, and m_3. Hospital A_1 is the focal hospital. Hospital B_1 belongs to chain $\mathbb{B}$, the rest of whose members, $\{B_2, B_3, B_4, B_5\}$, are located in markets m_2 and m_3.

Figure A9: Example of how to construct instruments for system share



Note: Example of how to construct the instruments for the system share variable. There are three markets: m_1, m_2, and m_3. Hospital A_1 is the focal hospital, along with A_2 belonging to chain $\mathbb{A}$, whereas B_1, B_2, B_3, and B_4 belong to chain $\mathbb{B}$.

Table A1: Top 11 EMR vendors and their national market share (%)

Year	Self-developed	Cerner	CPSI	Healthland	Eclipsys	Epic	GE	HMS	McKessons	Siemens	Meditech	Total
2005	8.87	10.93	4.76	0.87	3.35	1.57	0.22	1.62	13.91	12.01	30.25	88.37
2006	7.63	11.67	5.68	1.91	3.90	2.00	3.33	2.31	12.64	11.85	29.10	92.01
2007	6.29	11.27	8.05	3.46	3.33	3.29	2.79	3.09	11.07	10.61	28.07	91.32
2008	5.46	11.22	8.42	3.95	3.39	3.95	2.51	3.01	11.13	9.64	28.40	91.09
2009	4.76	11.53	8.24	4.31	3.48	5.73	2.30	4.26	12.03	9.15	26.91	92.70
2010	4.67	11.93	8.81	4.21	3.50	7.61	2.07	4.32	11.24	8.63	25.87	92.85
2011	4.36	12.39	9.10	4.56	3.07	10.16	1.12	4.61	10.95	7.91	24.98	93.21
2012	4.57	12.89	8.97	4.69	2.95	12.63	0.80	4.72	10.33	7.09	23.61	93.25
2013	4.08	13.99	8.87	4.53	2.68	16.24	0.66	5.05	10.05	6.40	22.57	95.12
2014	3.26	16.36	8.80	4.12	2.37	19.06	0.44	4.86	8.40	5.86	21.67	95.21

Note: Calculation is based on all hospitals, including stand-alone and affiliated hospitals in 2005-2014.

Table A2: Actual products offered by leading vendors

Vendor	Major inpatient EMR "suite"	Associated products
Cerner	Millennium	**Open Clinical Foundation**, part of Millennium, is an enterprise-wide, relational database with multimedia capabilities that capture data from various sources and supports data extraction for medical research.[49] **Pharmnet**, part of Millennium, is the pharmacy information system.[50] **PowerInsight** is an operational reporting platform built on Millennium.[51]
CPSI	ChartLink	–
Healthland	Centriq	**Advanced Professional Software** specializes in financial software, such as financial management, resource management, physician practice management, and clinical information management.[52] **American Healthnet** offers enterprise information systems to community healthcare facilities.[53] Both will be integrated into the Healthland's health information system.
Eclipsys	Sunrise	**TDS** was acquired by Alltel in 1993 and then purchased by Eclipsys in 1997.[54] **EMTEK** was acquired by Eclipsys in 1998.[55]. Eclipsys interfaced Emtek Continuum 2000 point of care software with its TDS 7000 clinical system and marketed the system with its SunSuite client/server applications.[56] **Sungard** was purchased by Eclipsys in 1999,[57] which offered leading-edge document imaging technology and workflow solutions.[58] **EPSI**, a leading business decision support and budgeting system, was acquired by Ecliypsys in 2008.[59] Its solutions are similar to Eclipsys, which enables Eclipsys to immediately incorporte the technology.[60]

[49] https://www.encyclopedia.com/books/politics-and-business-magazines/cerner-corporation

[50] https://cernercorporation.gcs-web.com/news-releases/news-release-details/cerners-hna-millenniumr-solution-earns-technology-award

[51] https://boristyukin.com/healthcare-analytics-with-cerner-part-1-data-acquisition/

[52] https://www.redorbit.com/news/health/1555591/dairyland_healthcare_solutions_changes_name_to_healthland_and_acquires_advanced/

[53] https://tcbmag.com/local-health-it-firm-healthland-acquires-software-co/

[54] https://www.hcinnovationgroup.com/home/article/13013247/greatgrandfather-of-cpoe

[55] https://www.wikiwand.com/en/Eclipsys

[56] https://www.hcinnovationgroup.com/home/article/13012909/industry-watch

[57] https://www.reliasmedia.com/articles/117720-eclipsys-to-pay-25-million-for-intelus-med-data-systems

[58] https://www.reliasmedia.com/articles/117720-eclipsys-to-pay-25-million-for-intelus-med-data-systems

[59] https://www.healthcareitnews.com/news/eclipsys-announces-epsi-acquisition-himss08

[60] https://www.finanznachrichten.de/nachrichten-2008-02/10191048-eclipsys-acquires-enterprise-performance-systems-inc-epsi-extends-leadership-with-business-performance-improvement-solutions-004.htm

Vendor	Major inpatient EMR suite	Associated products
Epic	EpicCare	**Enterprise** includes a series of enterprise applications to serve different management purposes for the organization, such as revenue cycle management, financial management, supply chain management, etc.[61] **EpiCente**r is part of EpicCare, which can be used to improve population management.[62] **Excellian** is an Minneapolis-based Allina Health System's version of EpicCare.[63]
GE	Centricity	**CareCast** and **LastWord** are the predecessors of Centricity.[64] **MedicaLogic** was acquired by GE in 2002, mainly in the outpatient setting, thus helping GE expand to the outpatient market.[65]
HMS	HMS (Monitor)	**Medhost**, a developer of emergency department systems, was acquired by HMS's parent company in 2010.[66]
McKesson	Horizon for large hospitals and Paragon for community hospitals. From 2011, McKesson decided to move from Horizon to Paragon[67]	**Acumax** is a wholesale distribution service in the field of pharmaceuticals, featuring an automated warehouse inventory and distribution system utilizing bar code scanning technology.[68] **STAR** and **HealthQuest** are both revenue cycle solutions.[69] **Interqual** is McKesson's flagship decision support solution.[70] **Pathways** is for enterprise resource managements.[71] **Per-Se** was acquired by McKesson in 2006, specializing in financial and administrative healthcare solutions for hospitals, physicians, and retail pharmacies.[72] **Saint Express** and **SERIES** are old systems and are predecessors of Paragon.[73]

[61] https://www.appsruntheworld.com/cloud-top-500-applications-vendors/epic-systems/

[62] http://caph.org/wp-content/uploads/2014/12/Whole-Person-Care_Target-Population_Marocco_PPT.pdf

[63] https://www.beckershospitalreview.com/healthcare-information-technology/4-latest-epic-go-lives.html?oly_enc_id=7109B1429678J1B

[64] https://www.itnonline.com/content/health-system-gets-%E2%80%9Clastword%E2%80%9D-ge%E2%80%99s-centricity

[65] https://www.bizjournals.com/milwaukee/stories/2002/03/25/daily9.html

[66] https://www.limswiki.org/index.php/MEDHOST,_Inc.

[67] https://www.healthdatamanagement.com/articles/mckesson-puts-brakes-on-horizon-revenue-app-doubles-down-on-paragon

[68] https://trademarks.justia.com/742/72/acumax-74272932.html

[69] https://www.mckesson.com/About-McKesson/Newsroom/Press-Releases/2017/Allscripts-to-acquire-McKessons-Enterprise-Information-Solutions-Business/

[70] https://www.businesswire.com/news/home/20160314005330/en/McKesson-InterQual-Connect-Creates-Connected-Ecosystem-for-Medical-Review-and-Authorization

[71] https://www.theinformaticsgroup.com/mckesson/

[72] https://www.blackstone.com/news/press/mckesson-to-acquire-per-se-technologies-for-1-8-billion/#:$\sim$:text=Per%2DSe%20Technologies%20(NASDAQ%3A,administrative%20burden%20of%20providing%20healthcare

[73] https://www.slideshare.net/hiospros/122-mckesson-10-end-30595765

Vendor	Major inpatient EMR suite	Associated products
Siemens	Soarian	Both **INVISION** and **MedSeries4** focus more on the revenue cycle management, with MedSeries4 targeting rural and community hospitals.[74] **Lifetime Clinical Record** is part of INVISION, creating a single, growing patient record of all information collected across the organization.[75] **NOVIUS** is a laboratory information systems.[76]
Meditech	MAGIC, Client/Server (both using the same programming language, with the main difference lying in the type of servers running the codes)[77]	

[74] https://klasresearch.com/Content/PDF/Marketing/Cerner%20-%20Siemens%20Powerpoint.pdf
[75] https://excitehealthpartners.com/insight-learning/siemens-health-it-solutions/
[76] https://www.siemens-healthineers.com/en-us/news/novius-named-best-in-klaus-02-03-2012.html
[77] https://en.wikipedia.org/wiki/Meditech

Table A3: Summary statistics for hospital variables by adoption status—IV sample

New or never adopters	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# outside associated markets	3.4	3.5	3.6	3.7	3.7	3.5	3.6	3.4	3.4	3.4
# associated chains	6.3	6.5	6.1	6.3	6	6.1	6.2	6.7	5.7	5.4
% whose chosen vendor is system-dominant	3.5	20.3	36.8	50.7	58	60.9	65.6	64.1	75.7	73.5
% whose chosen vendor is market-dominant	4.9	11.4	17.2	26.8	28.1	32.7	33.9	31.3	37.2	43.1
% ever not-for-profit hospitals	54.3	54.1	56.8	57.2	57.7	62.9	61.7	57.9	57.8	57.5
% ever teaching hospitals	3.5	3.26	3.34	3.14	2.99	3.32	3.33	3.1	3.17	3.31
# beds	198	200	202	201	205	218	219	212	211	211
% affiliated ambulatory care facilities in the same market	10.7	10.4	11	10.4	10.3	11.4	11.6	11.1	8.2	9.1
% affiliated subacute care facilities in the same market	9.03	9.33	10.1	9.75	9.79	10.9	11.6	10.2	7.73	8.19
Total # affiliated hospitals	429	429	419	414	402	361	360	387	379	362
Experienced adopters	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# outside associated markets	3.3	3.7	3.8	4.2	4.3	3.8	4	3.7	3.8	3.6
# associated chains	8.6	8.1	8.7	8.4	8.7	7.1	7.5	8.5	10.4	9.7
% whose chosen vendor is system-dominant	79.87	81.4	83.5	76.8	76.5	78.9	77.7	77.9	78.5	70.5
% whose chosen vendor is market-dominant	41.2	44.7	45.6	42.8	38	38.4	39.2	37.2	34	41.1
% ever not-for-profit hospitals	30.2	28.9	33	37.9	39.3	41.2	41.9	44.5	46	48.4
% ever teaching hospitals	3.25	2.83	2.75	2.72	3.74	4.77	4.9	4.65	4.79	4.88
# beds	210	204	203	205	214	212	211	214	218	220
% affiliated subacute care facilities in the same market	9.71	8.53	7.99	11.6	10.8	10.4	11	11.9	10.2	11.1
% affiliated ambulatory care facilities in the same market	10.0	9.01	9.92	13.9	12.5	12.9	12.8	12.4	11.0	11.4
Total # affiliated hospitals	308	318	327	367	374	398	408	452	480	492

Note: Table reports the mean value of statistics over the years 2005-2014.

Table A4: Summary statistics for chain/market variables—IV sample

Chain characteristics	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# affiliated hospitals	22.6	21.7	22.6	23.1	22.9	22.3	23.2	22.7	24	24.8
# beds	4,214	4,014	4,171	4,245	4,342	4,334	4,505	4,346	4,572	4,734
# markets	16	15	15	16	16	15	15	15	16	16
# leading vendors	1.3	1.4	1.8	2	2.4	2.6	2.4	2.2	2.2	2.3
# ambulatory care facilities	64	63	54	65	89	98	110	110	147	159
# subacute care facilities	20	17	17	16	16	12	13	13	15	15
Total # chains	52	55	53	53	53	54	51	56	54	53
Market characteristics	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# stand-alone hospitals	3.5	3.5	3.5	3.4	3.3	3	3	2.9	2.7	2.7
# affiliated hospitals	7.5	7.6	7.6	7.7	7.6	7.7	7.9	7.7	7.5	7.5
# leading vendors	2	2.3	2.9	3.2	3.5	3.5	3.6	3.6	3.6	3.6
# chains	4.3	4.4	4.3	4.3	4.3	4.3	4.3	4.2	4.1	4.1
Population over 65	107,786	108,292	109,577	112,420	114,197	118,083	122,623	121,435	121,923	126,470
HHI	0.28	0.28	0.28	0.28	0.29	0.29	0.29	0.30	0.30	0.30
Total # markets	173	174	175	181	183	179	173	187	195	196

Note: Table reports the mean value of statistics over the years 2005-2014.

Table A5: Comparing hospital characteristics between the merged dataset and AHA data

	AHA data	Merged dataset
Bed size	158	168
Total admissions	6,211	7,414
% teaching hospital	6.09	6.47
% not-for-profit	50.9	59.7
% for-profit	22.3	17.1
% Medicare discharge	44.4	48.6
% Medicaid discharge	15.4	16.9
% affliiated hospitals	55.5	55.8
# hospitals	5,968	4,556

Note: Table reports the mean value of statistics over the years 2005-2010. I use a shorter time period because the AHA data is only available in this timeframe.

Table A6: Effect from share variables that are adjusted by number of beds

	New adopter			Experienced adopter		
	All	IV sample		All	IV sample	
	Logit	Logit	CF	Logit	Logit	CF
	(1)	(2)	(3)	(4)	(5)	(6)
System share	2.636***	2.983***	4.819***	1.589***	2.254***	4.013***
	(0.173)	(0.274)	(0.383)	(0.128)	(0.265)	(0.295)
Market share	0.464***	0.713**	0.458	-0.0529	0.170	0.747**
	(0.150)	(0.329)	(0.465)	(0.111)	(0.210)	(0.303)
Chosen previously				4.061***	3.854***	3.872***
				(0.0891)	(0.152)	(0.0738)
MEs (%): *System* share	18.7***	21.2***	34.2***	12.1***	17.2***	30.7***
	(1.23)	(1.95)	(2.72)	(0.981)	(2.03)	(2.25)
MEs (%): *Market* share	3.30***	5.06**	3.25	-0.404	1.30	5.71***
	(1.06)	(2.34)	(3.30)	(0.850)	(1.60)	(2.31)
N	56,147	20,527	20,527	251,940	76,224	76,224
Pseudo R^2	0.624	0.639	0.641	0.838	0.866	0.868
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$			6.45e-06			8.74e-13

Note: Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses. Standard errors clustered at the chain level for logit regressions and bootstrapped standard errors (based on 50 replications) for the CF approach.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effect from share variables, based on HRRs

	New adopter			Experienced adopter		
	All	IV sample		All	IV sample	
	Logit	Logit	CF	Logit	Logit	CF
	(1)	(2)	(3)	(4)	(5)	(6)
System share	2.760***	3.274***	4.953***	1.634***	2.514***	4.198***
	(0.168)	(0.284)	(0.313)	(0.132)	(0.244)	(0.227)
Market share	0.535**	0.808**	1.921***	-0.0665	0.404	4.175***
	(0.224)	(0.393)	(0.667)	(0.219)	(0.401)	(1.147)
Chosen previously				4.033***	3.776***	3.795***
				(0.0857)	(0.130)	(0.0740)
MEs (%): *System* share	19.6***	23.2***	35.2***	12.5***	19.2***	32.1***
	(1.19)	(2.02)	(2.22)	(1.01)	(1.86)	(1.74)
MEs (%): *Market* share	3.80**	5.73**	13.6***	-0.508	3.09	31.9***
	(1.59)	(2.79)	(4.74)	(1.67)	(3.06)	(8.76)
N	57,135	25,454	25,454	251,124	90,252	90,252
Pseudo R^2	0.593	0.664	0.667	0.838	0.855	0.858
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$			2.50e-06			1.48e-14

Note: Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses. Standard errors clustered at the chain level for logit regressions and bootstrapped standard errors (based on 50 replications) for the CF approach.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Effect from share variables, by defining markets based on a 45 mile radius

	New adopter			Experienced adopter		
	All	IV sample		All	IV sample	
	Logit	Logit	CF	Logit	Logit	CF
	(1)	(2)	(3)	(4)	(5)	(6)
System share	2.697***	3.223***	4.819***	1.609***	2.369***	3.791***
	(0.171)	(0.136)	(0.335)	(0.132)	(0.251)	(0.289)
Market share	0.861***	0.544	0.594	0.159	0.341	1.117***
	(0.199)	(0.349)	(0.733)	(0.227)	(0.486)	(0.347)
Chosen previously				4.017***	3.768***	3.812***
				(0.0858)	(0.139)	(0.0977)
MEs (%): *System* share	19.1***	22.9***	34.2***	12.3***	18.1***	29.0***
	(1.21)	(0.966)	(2.38)	(1.01)	(1.91)	(2.21)
MEs (%): *Market* share	6.11***	3.86	4.22	1.21	2.61	8.53***
	(1.41)	(2.48)	(5.21)	(1.74)	(3.71)	(2.65)
N	56,147	18,005	18,005	251,940	66,984	66,984
Pseudo R^2	0.628	0.642	0.645	0.838	0.863	0.863
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$			2.71e-05			5.02e-09

Note: Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses. Standard errors clustered at the chain level for logit regressions and bootstrapped standard errors (based on 50 replications) for the CF approach.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Effect from share variables, based on the years 2006–2010

	New adopter			Experienced adopter		
	All	IV sample		All	IV sample	
	Logit (1)	Logit (2)	CF (3)	Logit (4)	Logit (5)	CF (6)
System share	2.620***	3.125***	4.302***	1.527***	1.688***	3.013***
	(0.0800)	(0.145)	(0.457)	(0.152)	(0.388)	(0.388)
Market share	0.443***	0.626**	0.425	-0.0853	0.00619	1.780***
	(0.137)	(0.303)	(0.483)	(0.204)	(0.618)	(0.415)
Chosen previously				4.100***	4.127***	4.156***
				(0.111)	(0.234)	(0.153)
MEs (%): *System* share	18.6***	22.2***	30.5***	11.7***	12.9***	23.0***
	(0.568)	(1.03)	(3.25)	(1.16)	(2.97)	(2.96)
MEs (%): *Market* share	3.15***	4.45**	3.02	-0.652	0.0473	13.6***
	(0.976)	(2.15)	(3.43)	(1.56)	(4.72)	(3.17)
N	50,739	18,187	18,187	130,980	37,740	37,740
Pseudo R^2	0.634	0.651	0.652	0.841	0.874	0.877
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$			0.0417			7.39e-06

Note: Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses. Standard errors clustered at the chain level for logit regressions and bootstrapped standard errors (based on 50 replications) for the CF approach.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Effect from share variables, conditional on adoption/switching

	New adopter			Experienced adopter		
	All	IV sample		All	IV sample	
	Logit	Logit	CF	Logit	Logit	CF
	(1)	(2)	(3)	(4)	(5)	(6)
System share	3.399***	3.623***	3.960***	4.188***	5.150***	6.597***
	(0.231)	(0.407)	(0.598)	(0.316)	(0.654)	(0.732)
Market share	0.636***	0.729*	0.910	0.172	0.664	1.531**
	(0.192)	(0.420)	(0.561)	(0.241)	(0.523)	(0.703)
MEs (%): *System* share	26.0***	27.7***	30.2***	34.6***	42.6***	54.5***
	(1.77)	(3.11)	(4.57)	(2.61)	(5.40)	(6.05)
MEs (%): *Market* share	4.86***	5.57*	6.95	1.42	5.49	12.7**
	(1.46)	(3.21)	(4.29)	(1.99)	(4.32)	(5.81)
N	14,124	5,088	5,088	20,394	5,324	5,324
r2_p	0.398	0.475	0.475	0.398	0.484	0.490
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$			0.878			0.0319

Note: Unit of observation is hospital/year. Analysis based on hospital-year observations with adoption/switching decisions, excluding the option of the current choice for the hospital. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Standard errors in parentheses. Standard errors clustered at the chain level for logit regressions and bootstrapped standard errors (based on 50 replications) for the CF approach.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Results of robustness checks for concerns related to endogeneity

	Modified IVs		Including impor--tant markets		Excluding indica--tor for switching
	New adopter (1)	Experienced adopter (2)	New adopter (3)	Experienced adopter (4)	Experienced adopter (5)
System share	4.219***	4.069***	4.806***	4.117***	4.415***
	(0.496)	(0.312)	(0.366)	(0.297)	(0.0895)
Market share	0.424	1.163***	0.489	0.977***	2.702***
	(0.438)	(0.366)	(0.379)	(0.302)	(0.166)
Chosen previously		3.999***		3.804***	
		(0.0976)		(0.0775)	
MEs (%): *System* share	30.0***	31.1***	34.1***	31.4***	33.7***
	(3.52)	(2.39)	(2.60)	(2.27)	(0.684)
MEs (%): *Market* share	3.01	8.89***	3.47	7.47***	20.6***
	(3.11)	(2.80)	(2.69)	(2.31)	(1.27)
N	16,653	58,956	23,179	85,092	75,900
Pseudo R^2	0.657	0.880	0.647	0.867	0.699
P-value for joint signi--ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$	0.0774	5.34e-15	3.14e-05	1.02e-14	8.78e-27

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors in parentheses (based on 50 replications).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Effect from share variables, robustness checks of adding more FEs/controls

	New adopter					Experienced adopter				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
System share	1.241***	4.961***	5.138***	5.111***	4.586***	4.278***	4.049***	4.299***	4.312***	4.139***
	(0.308)	(0.335)	(0.452)	(0.423)	(0.413)	(0.216)	(0.230)	(0.242)	(0.265)	(0.305)
Market share	-2.900***	1.165***	1.032**	0.938*	0.511	1.705***	1.473***	1.477***	1.467***	1.248***
	(0.388)	(0.407)	(0.418)	(0.493)	(0.554)	(0.300)	(0.334)	(0.309)	(0.270)	(0.380)
Chosen previously						3.587***	3.879***	3.768***	3.776***	3.839***
						(0.0583)	(0.0789)	(0.0815)	(0.0792)	(0.0840)
Vendor fixed effects	no	yes	yes	yes	yes	no	yes	yes	yes	yes
Hospital controls	no	no	yes	yes	yes	no	no	yes	yes	yes
Market controls	no	no	no	yes	yes	no	no	no	yes	yes
Vendor-specific trends	no	no	no	no	yes	no	no	no	no	yes
MEs (%): *System* share	8.81***	35.2***	36.5***	36.3***	32.6***	32.7***	30.9***	32.8***	32.9***	31.6***
	(2.19)	(2.38)	(3.21)	(3.00)	(2.94)	(1.65)	(1.75)	(1.85)	(2.03)	(2.33)
MEs (%): *Market* share	-20.6***	8.27***	7.33**	6.66*	3.63	13.0***	11.3***	11.3***	11.2***	9.53***
	(2.76)	(2.89)	(2.97)	(3.50)	(3.93)	(2.29)	(2.55)	(2.36)	(2.06)	(2.90)
N	20,007	20,007	20,007	20,007	20,007	75,900	75,900	75,900	75,900	75,900
Pseudo R^2	0.0350	0.622	0.632	0.635	0.645	0.846	0.860	0.868	0.868	0.870
P-value for joint signi--ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$	2.12e-08	6.63e-07	7.03e-05	4.16e-06	0.00306	8.47e-22	1.01e-16	4.75e-19	9.02e-17	1.55e-12

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors in parentheses (based on 50 replications).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Effect from share variables, by HHI

	New adopter		Experienced adopter	
	Competitive (1)	Concentrated (2)	Competitive (3)	Concentrated (4)
System share	5.396***	3.904***	3.648***	4.214***
	(0.610)	(0.618)	(0.346)	(0.333)
Market share	2.821***	-0.440	1.797***	0.609
	(1.048)	(0.681)	(0.548)	(0.394)
Chosen previously			3.925***	3.821***
			(0.133)	(0.103)
MEs (%): *System* share	38.3***	27.7***	27.9***	32.2***
	(4.33)	(4.39)	(2.65)	(2.54)
MEs (%): *Market* share	20.0***	-3.12	13.7***	4.65
	(7.44)	(4.84)	(4.19)	(3.01)
N	9,529	10,478	38,064	37,836
Pseudo R^2	0.649	0.651	0.873	0.863
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$	1.27e-06	0.0614	5.68e-08	4.12e-05

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors in parentheses (based on 50 replications).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Effect from share variables, by total 65+ population

	New adopter		Experienced adopter	
	Small	Large	Small	Large
	(1)	(2)	(3)	(4)
System share	3.914***	5.324***	3.994***	4.002***
	(0.565)	(0.696)	(0.363)	(0.384)
Market share	0.174	1.691	0.676*	1.927***
	(0.608)	(1.144)	(0.384)	(0.556)
Chosen previously			3.820***	3.885***
			(0.117)	(0.130)
MEs (%): *System* share	27.8***	37.8***	30.5***	30.6***
	(4.01)	(4.94)	(2.77)	(2.94)
MEs (%): *Market* share	1.23	12.0	5.16*	14.7***
	(4.32)	(8.12)	(2.93)	(4.25)
N	10,686	9,321	38,040	37,860
Pseudo R^2	0.647	0.639	0.864	0.872
P-value for joint signi- -ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$	0.437	0.00277	2.13e-06	1.69e-08

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Unit of observation is hospital/year. Other regressors include the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors in parentheses (based on 50 replications).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Effect from share variables, by relative bed size

	New adopters	Experienced adopters
System share	4.649***	4.172***
	(0.392)	(0.303)
Market share	0.616	1.318***
	(0.587)	(0.394)
Interacted with *system* share	-4.793***	-1.786**
	(1.849)	(0.751)
Interacted with *market* share	3.549	-1.459
	(4.226)	(1.105)
Chosen previously		3.827***
		(0.0838)
MEs (%): *System* share	33.0***	31.9***
(baseline)	(2.78)	(2.31)
MEs (%): *System* share	-1.65***	-0.631**
(extra)	(0.638)	(0.265)
MEs (%): *Market* share	4.37	10.1***
(baseline)	(4.17)	(3.01)
MEs (%): *Market* share	1.22	-0.516
(extra)	(1.46)	(0.390)
N	20,007	75,900
Pseudo R^2	0.642	0.870
P-value for joint signi-	0.0243	6.62e-11
-ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$		

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Other regressors include the moderator variable, the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors (based on 50 replications) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A16: Effect from the number of healthcare facilities on vendor market share

	Dependent variable: Vendor market share	
Total # providers	-0.0000250***	
	(0.00000841)	
EMR HHI		0.0278***
		(0.00336)
N	330,174	330,174

Note: Unit of observation is hospital/year. Other regressors include vendor system share, vendor fixed effects, market and year fixed effects. Standard errors in parentheses, clustered at the market level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A17: Effect from share variables, by CMI

	New adopters	Experienced adopters
System share	4.099***	4.092***
	(0.570)	(0.246)
Market share	0.820	1.292***
	(0.580)	(0.449)
Interacted with *system* share	0.000272	-0.0000276
	(0.000200)	(0.0000355)
Interacted with *market* share	-0.000307	0.0000108
	(0.000422)	(0.0000782)
Chosen previously		3.876***
		(0.101)
MEs (%): *System* share	29.1***	31.3***
(baseline)	(4.04)	(1.88)
MEs (%): *System* share	2.14	-0.418
(extra)	(1.57)	(0.538)
MEs (%): *Market* share	5.82	9.87***
(baseline)	(4.12)	(3.43)
MEs (%): *Market* share	-2.41	0.164
(extra)	(3.31)	(1.18)
N	13,078	53,676
r2_p	0.686	0.866
P-value for joint signi-	0.217	3.58e-13
-ficance of $\hat{e}^{\text{mkt}}$ and $\hat{e}^{\text{sys}}$		

Note: Analysis applying the CF approach to the IV sample, with instruments specified in Section 4. Unit of observation is hospital/year. Other regressors include the moderator variable, the not-for-profit indicator, teaching hospital indicator, market-category effects, HHI, the elderly population at the market level, vendor-specific time trends, vendor fixed effects, and vendor dummies interacting with number of beds. Bootstrapped standard errors (based on 50 replications) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$